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HUMAN JUDGMENT AND DECISION MAKING:

A PROPOSED DECISION MODEL

USING SEQUENTIAL PROCESSING

A Dissertation

Presented to

the Graduate School of

Clemson University

In Partial Fulfillment

of the Requirements for the Degree

Doctor of Philosophy

Engineering Management

by

Wade H. Shaw, Jr.

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200 Stovall Street
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This research effort developed, discussed and tested an alternative model of human judgment. Previous research has established the robustness and explanatory power of the linear compensatory decision model and documented evidence indicating a fundamental inability of the brain to process decision cue interactions. This research used policy capturing experiments to simulate human decision making in order to determine the explanatory power of a decision model based on processing decision cues in a sequential, →over cumulative fashion. This model is nonlinear and expands the limitations of previous decision models. A primary concern was the selection of weights used in ~~the~~ either the compensatory or proposed decision models. Subjective weights supplied by the participants in two decision making exercises were compared with weights estimated for each model and with equally weighted cues. An analysis of variance was completed to determine the performance of the alternative models with each set of weights. It was concluded that the proposed decision model is a valid and innovative model of human judgment, particularly when equally weighted cues are used. The implications of a sequential model of judgment are discussed and applications to other research disciplines are presented.

Human Judgment and Decision Making: A Proposed Decision Model using Sequential Processing

Wade H. Shaw, Jr., CPT, US Army
HQDA, MILPERCEN (DAPC-OPA-E)
200 Stovall Street
Alexandria, VA 22332

August 2, 1985

A thesis submitted to Clemson University, Clemson, South Carolina in partial fulfillment of the requirements for the degree of Doctor of Philosophy with a major in Engineering Management.

August 2, 1985

To the Graduate School:

Herewith is submitted a dissertation written by Wade H. Shaw, Jr. entitled "Human Judgment and Decision Making: A Proposed Decision Model Using Sequential Processing." I recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Engineering Management.

Dissertation Advisor

We have reviewed this dissertation and recommend its acceptance:

R. Lawrence LaForge

E. Ernest Burch

Accepted for the Graduate School:

Farrell P. Brown

HUMAN JUDGMENT AND DECISION MAKING: A PROPOSED DECISION MODEL USING SEQUENTIAL PROCESSING

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ABSTRACT

This research effort developed, discussed, and tested an alternative model of human judgment. Previous research has established the robustness and explanatory power of the linear compensatory decision model and documented evidence indicating a fundamental inability of the brain to process decision cue interactions. This research used policy capturing experiments to simulate human decision making in order to determine the explanatory power of a decision model based on processing decision cues in a sequential, cumulative fashion. This model is nonlinear and expands the limitations of previous decision models. A primary concern was the selection of weights used in either the compensatory or proposed decision model. Subjective weights supplied by the participants in two decision making exercises were compared with weights estimated for each decision model and with equally weighted cues. An analysis of variance was completed to determine the performance of the alternative models with each set of weights. The mean squared error of prediction and the squared bivariate correlation between predicted and actual decisions were the performance measures. It was concluded that the proposed decision model is a valid and innovative model of human judgment, particularly when equally weighted cues are used. The implications of a sequential model of judgment are discussed and applications to other research disciplines are presented.

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CHAPTER I

INTRODUCTION

Decision making involves making choices between competing alternatives. Usually limitations on available resources require that the decision maker must choose an alternative which satisfies the resource requirements while maximizing some set of objectives. Viewed in this manner decision making takes on economic dimensions as well as psychological.

The objective of this research is to better understand the decision making process by comparing a proposed decision making model against a model previously demonstrated as being a useful and particularly robust model. The proposed model is a refinement of the linear compensatory model which depicts a decision as the sum of weighted explanatory criteria. The purpose of the research is to compare the explanatory power of the proposed model in order to better understand the mental processes involved in decision making.

Decision making is a complex and relatively new discipline of study. The core of effective management is built on valid and reliable decision making. Since decisions must be made at all levels of private, government and corporate organizations and across virtually all functional areas, an understanding of the decision making process is fundamental in achieving higher management effectiveness and efficiency. The fields of management science, operations research and systems analysis each seek to provide some means of achieving better decisions. The currently popular management information systems, decision support systems and computer models are efforts to provide timely and accurate information to decision makers. The economic cost of poor decisions is impossible to calculate but certainly enormous. Yet, with all of these disciplines, techniques and equipment the key element, the decision maker, is still not well understood.

A number of general decision making models have been proposed as representative of the way in which information is processed in human decision making (Bross, 1953). These models form the basis for decision rules which are intended to aid the decision maker. One such rule is the disjunctive type strategy. This rule bases a decision on a single outstanding characteristic and excludes all other information. A conjunctive rule uses all information and requires that all decision factors exceed some minimal requirement. Typically this method is referred to as a "multiple hurdles" method. An alternative to these rules is the compensatory decision rule. A compensatory rule generates an overall judgment based on the combined effects of all decision factors. In this model poor performance on one criteria may be overcome by better performance on other criteria.

The compensatory model is often formulated as the weighted sum of each decision criteria, where the weights are assigned in accordance with the decision maker's concern for each particular factor. A primary concern then is determining the weights which yield the most valid and acceptable decisions.

These basic decision rules are applicable in a wide variety of decision making environments. The scientific principle of parsimony, that is, keeping things simple, is applicable in the modeling of decision making. Numerous models derived from the basic three approaches have been postulated (Hammond, McClelland and Mumpower, 1980). Most research in this area has determined that simple linear compensatory models have been as effective as other more complex models (Beach, 1967; Darlington, 1968; Dawes and Corrigan, 1974).

The basic linear compensatory model is given as:

$$Y_j = \sum_{i=1}^{n} B_i X_{ij}, \qquad j = 1 \text{ to } m \tag{1}$$

where

Y_j = the decision or rating,

B_i = the beta weight or importance attributed to information cue or criterion X_{ij}, typically derived from regression analysis,

X_{ij} = the information cue or criterion,

n = the number of cues (i),

m = the number of decision alternatives (j).

The beta weight is equivalent to the standardized regression coefficient. To compare decision makers the beta weights can be transformed into relative weights (RW_i). These relative weights represent the relative importance of a cue compared to other cues in the model. Relative weights sum to one. Calculation of the RW_i's is presented in the research methodology.

The key questions addressed by any decision model are threefold. What information is actually used in making a decision? What is the relative importance of each piece of information? How is the information combined to reach a decision? A technique developing in the management science and organizational behavior fields that formulates a decision model with respect to the issues noted above is called policy capturing (Szilagyi and Wallace, 1983).

The purpose of policy capturing is to develop a decision making model which explains the implicit strategy a decision maker uses. The development of the model then makes the strategy explicit and hopefully aids the decision maker in making more consistent and higher quality decisions. The theory is that one can "capture" the policy used by a decision maker by observing past or simulated decisions and then predict a decision based on the derived decision model and the information available to the model.

Statement of the Problem

Although previous research, as discussed in the literature review, has established the robustness and explanatory power of linear compensatory decision models, several weaknesses exist. The compensatory model by definition allows poor performance in some criteria to be compensated for by better than average performance in other criteria. While this is a desirable feature, it means that there are an infinite number of combinations of weighted criteria which yield the same decision. This is particularly troublesome when the alternative choices are mutually exclusive. In this case alternatives may achieve equal overall ratings but in very different ways. How then are they to be distinguished? Or the alternatives may achieve very nearly the same rating and yet the combination of criteria be very different. This is particularly true when the criteria weights vary significantly.

A second notable weakness is the assumption of perfect and instantaneous information. By perfect it is meant that the decision maker faces no ambiguity in the criteria nor do the criteria take on probability distributions. Furthermore, the information, that is, cues or criteria, are evaluated instantaneously to derive a decision. The specification of the linear compensatory models makes no distinction in the ordering of the criteria-weight combinations. In fact, the application of multiple regression makes the assumption that no rank ordering is taking place. While the model, as shown, has been shown to explain a large portion of the variability in decision making, it is difficult to justify the assumption that the human brain can instantly process combinations of cues and weights. It seems more appealing to view the brain as a processor that analyzes combinations of cues and weights in some order (probably by weight) so that information is brought in sequentially.

A final weakness of the linear compensatory model is that it cannot be used to compare alternatives if the weights are altered. This situation could arise when the alternatives are very different in nature and their overall desirability is dependent upon a particular set of weights. In this case the decision model as stated could not be used to compare the alternatives since a "standard" set of weights is assumed. An example of this problem occurs in strategic planning when the decision is whether or not to acquire a firm. If the firms being compared are in different industries the weights in the decision model may vary to account for strengths and weaknesses in the particular industry. Therefore, it is difficult to compare alternative firms even though the decision models are good models within the particular industry.

Proposed Scoring Rule

At this point an alternative compensatory model is outlined without resorting to mathematical derivation. It is intended to be an overview of the method based on heuristic arguments. The mathematical development of the model is presented in the research methodology.

The proposed model incorporates the criteria-weight combinations and a sequential analysis technique where each criteria-weight factor is brought into the model in the order of the weights from high to low. The rationale motivating this approach is that the brain as a processor does not process information instantaneously but rather in sequential fashion. It seems reasonable that those criteria with highest weight should be considered first. The process of bringing criteria-weight combinations into the model yields a decaying rating from the rating of an alternative whose criteria are scored as perfect. That is, the model derives a measure of how far away from perfection a given alternative is given a set of criteria and weights where the highest weighted criteria are considered first.

Since the model is comparing an alternative against a perfect alternative the model's rating can be normalized by the worst case rating derived by setting criteria at their worst value and applying the criteria-weights as before. This approach allows the decision maker to view the progress of reaching the decision, not just the final rating.

The weaknesses of the linear compensatory model are thus overcome. First, the decayed rating from perfection depicts the progression from a perfect alternative to the alternative being considered. The situation where alternatives are given equal ratings is still possible but the progression to that rating can be inspected to further analyze the alternatives. The implication of instantaneous information processing is relaxed to allow sequential processing of criteria. Finally, the use of worst case normalization allows alternatives with different sets of weights to be compared since the decision model yields a rating of the alternative versus perfection given a worst case environment.

The application of the proposed model is a simple restructuring of the use of criteria-weight combinations. The basic theory of decision making is in no way altered except in the use of sequential information processing. The proposed model can be implemented in a similar fashion as the linear compensatory model and requires no sophisticated mathematical calculations or elaborate computing equipment.

Choice of Weights

If information is to be weighted and then combined in some fashion then a critical question is what set of weights to use. Certainly decision makers could specify the weights on a subjective basis but the researcher should expect sub-optimal model performance. In fact research done to date overwhelmingly supports the finding that human judges rarely know the importance they place on information even though the decision of interest may be a routine experience (Slovic, Fischhoff and Lichtenstein, 1977). An alternative is to estimate the weights based on sample decisions via a policy capturing experiment.

The estimation procedure, while well documented for the conventional linear model, is considerably more difficult in the nonlinear world where a sequential judgment model belongs. There are noteworthy complications which must be overcome, such as asymptotic properties of the estimators and the unknown nature of the response hyperspace.

The possibility also exists that the factors could be equally weighted. That is, each decision cue takes on equal value. Use of equal weights involves no effort to estimate them. If a model could be found which best uses equal weights, decision models would be much easier to implement. Evidence exists which indicates that equally weighted linear models perform quite well. The research issue, then, becomes which model, linear or sequential, best uses equal weights. The sequential model expects to see cues and weights in some order. Does it matter which order if the cues are weighted equally?

A more interesting question involves whether or not a human judge can rank order information better than he can place weights on them. It seems reasonable to believe that a decision maker may not estimate the weights well but may be able to determine the order in which information is of value. If equally weighted factors perform well in the linear model then they should be tested in the sequential model where the factors are brought in in subjectively ranked order. The equally weighted factors can also be brought into the sequential model in the order established by the weights estimated by the linear model regression. Would a difference in performance exist?

Finally it must be recognized that the order in which factor-weight combinations are brought into the sequential model will effect the estimated nonlinear weights. How then can the nonlinear weights be implemented into a decision model?

A fundamental concern of the research is to determine the effectiveness of a proposed sequential judgment model where the weights used are both estimated and specified a priori.

Objectives of the Research

The primary objective of this research is to compare the explanatory power of the proposed decision model and the linear compensatory decision model. The objective can be interpreted as a comparison of two theories concerning the internal processing of information within the brain. One theory, implemented via the linear compensatory model, explains decision making as the linear sum of decision criteria times their respective weights. The proposed theory is that decisions are made as a result of a sequential summing of criteria times weight that is compared against some internal threshold of acceptability.

To compare the predictive power of each decision model a decision making group will be sampled using a policy capturing experiment. The decision makers consist of farm owner/managers who make decisions each year concerning production of soybeans on their farms in South Carolina. To add validity to the research a separate and unrelated group of decision makers is used to compare the alternative models. Students are asked to complete a job selection exercise previously developed and validated. In this way some degree of cross validation is achieved and consistent findings yield more confidence in the research conclusions.

The production of soybeans represents a complex decision making situation with a high degree of risk. The decision is filled with uncertainty, large outlays of funds, and many competing decision criteria. The farm manager/owner must achieve decisions which allow continued survival. The use of very different decision making environments should provide suitable tests for comparing the alternative decision models.

A secondary objective of this research is to confirm that linear compensatory models are indeed effective in modeling the behavior of each decision making group. Also, it is desired to examine differences in decision making behavior across demographic and functional subsets of the original decision maker sample; e.g., large versus small soybean producers.

Research Hypotheses

The research hypotheses fall into two broad groups. The first group concerns establishing the explanatory power of the linear compensatory model as well as investigating any interactive effects of the compensatory model. Also the decision model differences between demographic/functional sub-groups within each set of decision makers will be tested. Finally, prior research has demonstrated a lack of insight on the part of the decision makers. That is, decision makers rarely know how they weight the decision criteria. By asking them their set of subjective weights, a statistical analysis can be completed to compare subjective weights with those estimated by regression techniques. This lack of insight is further evidence of the usefulness of decision models.

The second set of hypotheses is concerned with the comparison of the linear compensatory model with the proposed model. Two questions are significant. Is there a statistical difference in the explanatory power of the models? Is there a difference between the weights in either the compensatory model or the sequential judgment model? The overall goal of the research in answering these hypotheses is to determine if sequential decision models are justified and what set of weights are preferred given that a model has been specified.

The specific hypotheses are shown in Figure 1.

Individual Decision Making

H1: There is no statistically significant effect on the decision maker's ratings that is explained by the individual cues or interactive terms in either decision making exercise.

H2: There is no statistically significant difference between the decision maker's subjective cue weights and the relative weights derived from the compensatory model in either decision making exercise.

H3: There is no statistically significant difference in the linear regression models derived from the compensatory model among demographic/functional groups in either decision making exercise.

Comparison of Decision Models

H4: There is no statistically significant difference in the explanatory power of the proposed model and the linear compensatory model in either decision making exercise for equal, decision, nonlinear, relative, subjective, or subjectively ranked weights where each set of weights sum to one.

H5: There is no statistically significant difference in the explanatory power of equal, decision, nonlinear, relative, subjective, or subjectively ranked weights in either the linear or proposed decision model in either decision making exercise.

NOTE: Explanatory power is measured by the squared bivariate correlation between the predicted and actual ratings and by the mean squared error for each set of weights in each model.

Figure 1. Statement of the Hypotheses

Scope and Limitations of the Research

This research compares the explanatory power and decision maker preference of two compensatory decision models. One model is a historically validated model used in many prior research efforts. The second model is a proposed model designed to overcome several shortcomings of the older model. Both models are compared with the same set of criteria weights derived by regression methods or specified a priori. It is important to recognize that the use of policy capturing as a technique serves as a experimental test vehicle to provide human decisions in a simulated environment. This study is concerned with the alternative uses of the criteria-weight combinations once they are estimated or specified. If the criteria and weights were known a priori then a comparison of explanatory power could be accomplished directly.

This research accomplishes two basic objectives. First, the study adds validity to the policy capturing technique by adding to the list of decision maker groups analyzed by this technique. Second, the research uses the same set of decision makers and criteria weights to study a proposed theoretical decision model.

The limitations of the research result from the limited number of groups of decision makers and from the assumptions made in applying the policy capturing technique. Specifically, the technique of policy capturing assumes that the criteria selected adequately and objectively describe the decision making strategy of the individual. The criteria must be selected by careful discussion with individuals experienced in the particular decision being considered. Since an experiment must be designed with only a limited number of criteria it is recognized that the decision model is a simplification of a complex phenomenon. Furthermore, the effects of criteria or factors not included in the model are assumed to be random and normally distributed.

Finally, participation in the decision making exercise is voluntary making it possible for a degree of bias to exist in that only interested individuals might participate.

CHAPTER II

LITERATURE REVIEW

This chapter presents the basic theory used as the basis for this research. First the fundamental decision making process is presented. The concept of bounded rationality is developed as well as the concept of Human Information Processing (HIP). The theoretical basis of behavioral decision theory is summarized. Following this discussion is a review of significant findings based on regression analysis of policy capturing experiments.

The Decision Making Process

Four major dimensions of decision making have been identified (Bross, 1953). First a decision maker faces several alternatives regarding actions to be taken. A significant observation in current management thought is that there are always alternatives; perhaps not attractive options, but nevertheless, there are alternative courses of action.

Second, there exist outcomes as the result of each alternative which are different from each other. That is, each alternative generates results which can be distinguished from each other and have varying degrees of attractiveness or utility.

Third, each outcome has some chance or probability of occurring. That is, each outcome resulting from an alternative is viewed as a valid and possible result even though it may be with very low probability.

Finally, the decision maker makes a decision based on the value or economic utility of the outcome. It is recognized that different decision makers assign outcomes different values and probabilities of occurrence. Classical decision theory seeks to explain the use of information available to the decision maker in making choices among alternatives. A number of decision aids have developed from this approach to decision making. For example the Critical Path Method (CPM), inventory models, queuing models and goal programming are techniques developed in the management science field which attempt to tell decision makers how to make decisions. These models do not attempt to explain the process of decision making and are, therefore, referred to as normative decision models. The process of making a decision is addressed in the theory of behavioral decision theory.

Behavioral Decision Theory

Behavioral decision theory is a framework where decision theory and organizational theory are integrated to explain the process of decision making by individuals and groups (March and Simon 1958; Cyert and March 1963; Simon 1976). A fundamental concept in behavioral decision theory is that an ideal decision maker does not exist in practice and that decisions are made under conditions of bounded rationality (March and Simon, 1958).

Bounded rationality means that decisions are reached based on imperfect information and often without effort to obtain additional information that could be useful. The decision maker makes a decision only when the current alternative becomes unsatisfactory. Several conclusions can be derived from this theory.

First, decision making is not an effortless, spontaneous mental function. Decisions require effort and therefore motivation. Second, decision makers use the most accessible and convenient information and base decisions on possibly few criteria. Third, the final decision is heavily influenced by the decision maker's personal values, experience and background. Finally, bounded rationality implies that decisions are rarely optimal. That is, there is a tendency to satisfice rather than reach a decision which maximizes overall goal attainment.

Human Information Processing

A particularly significant area of research within the behavioral decision theory framework is the study of Human Information Processing (HIP). Numerous papers have been written on this general subject. A concise overview of this discipline is found in Szilagyi and Wallace (1983). Basically, decision models are developed which address three key issues mentioned previously in the introduction:

1. What information does the decision maker use?
2. What is the importance (weight) of each piece of information?
3. How is the information combined to reach a decision?

Several basic models have been proposed as presented in the introduction. Specifically,

1. Disjunctive Models: Decision strategy where information on a decision alternative is scanned to observe a single criterion sufficiently attractive enough to warrant its selection.

2. Conjunctive Models: Decision models where each criterion of the decision must meet or exceed some predetermined level.

3. Compensatory Models: Decision model where an overall judgment is reached by weighting each criterion and then summing up the individual components. The model is compensatory since low criterion values are compensated for by higher values of other criteria.

These decision models are fundamentally different views of the process of decision making. Each model has strengths and weaknesses and may generate very different decisions. No consensus among previous researchers exists as to the best model. Several convincing papers have presented evidence which supports the compensatory model (Dawes and Corrigan, 1974; Slovic, Fischoff and Lichtenstein, 1977).

Brunswick Lens Model

A prominent theory in behavioral decision theory is the Lens Model developed by Brunswick (1952,1956). This theory provides the basis for the application of linear additive models within the general compensatory decision model. Brunswick refers to a distal variable being the criterion or ultimate decision which may or may not be observable. Pieces of information about the distal variable are observable and are referred to as cues and are correlated with the distal variable. The correlation between the cue and the distal variable is defined as the validity of the cue. The decision maker observes these cues and integrates this knowledge in some manner to form an inference about the distal variable. The decision model can be expressed as:

$$Y_s = b_1X_1 + b_2X_2 + b_3X_3 + \dots + b_nX_n \tag{2}$$

where

Y_s = the inference made by the decision maker,

X_i = the standardized value of cue i,

b_i = the beta coefficients for cue i,

n = the number of observable cues.

Note the similarity to a regression model. The use of interactive terms may also be incorporated into the model. An interactive decision model with two-way interaction is given as:

$$Y_s = \sum_{i=1}^{n} b_i X_i + \sum_{j=2}^{n} \sum_{i=1}^{n-1} b_{ij} X_{ij}, \quad (j > 1) \tag{3}$$

where

b_{ij} = the beta coefficient for the two-way interaction of cues i and j.

Regression techniques can be used to estimate the beta weights and develop a decision policy when the cues and criteria are standardized. In this way the magnitudes of the beta weights can be used to compare individual decision makers. This technique will be discussed in a later section.

Brunswick's Lens Model has been extended into a number of decision making environments (Hammond, McClelland, and Mumpower, 1980). The Lens model has been actively implemented in a number of research efforts where behavioral decision theory is used to explain the decision making process (Einhorn and Hogarth, 1981; Slovic, Fischoff and Lichtenstein, 1977). The use of nonlinear compensatory models, that is, where interactive effects of criteria are included, has been undertaken (Goldberg, 1971).

The primary conclusion of research to date is that linear compensatory models are robust and effective predictors of human decision making. The use of regression and ANOVA techniques in conjunction with policy capturing experiments have successfully been able to generate compensatory decision models for a wide variety of decision making situations (Hammond, McClelland and Mumpower, 1980; Stahl and Zimmerer, 1983; Stahl and Harrell, 1983).

Compensatory Decision Models and Multiple Regression

A number of contributions to the use of statistical methods in developing decision models are significant. Hoffman (1960) developed the concept of a "relative weight," RW_i, which is calculated as:

$$RW_i = \frac{(b_i)^2}{R^2} \tag{4}$$

where

RW_i = the relative weight of cue i,

b_i = the beta weight of cue i determined by regression,

R^2 = the coefficient of determination of the multiple regression model.

Relative weights are valid when the cues are orthogonal, that is, linearly independent. The relative weights sum to unity (1) so that the term "relative" means the relative importance of each criteria. Ward (1962) and Darlington (1968) expanded the work of Hoffman to introduce the application of ANOVA techniques and simple correlation coefficients in orthogonal designs. Beach (1967) described the explanatory power of the compensatory model as well as Dawes and Corrigan (1974), Einhorn and Hogarth (1975), and Dawes (1979) to name a few.

Current findings of Stahl and Zimmerer (1983), Wallace (1983), Stahl and Harrell (1983) support the findings of previous research. The use of linear compensatory decision models have proved their validity in a number of decision making environments. Several research findings are noteworthy:

1. Linear compensatory models adequately explain a large portion of the variability in decisions reached by individual decision makers.

2. Decision makers do not assign subjective weights to cues that are statistically equivalent to estimated relative weights. This finding is the "lack of insight" phenomenon.

3. The interactive components of a compensatory decision model are not statistically significant. That is, the cues and their associated weights are significant in the model but the combined effects of two, three or more cues do not significantly affect the model. This observation sheds some insight on the inner processing power of the brain, since it seems that cues are not stored or processed instantaneously.

Ordering Effects

The ordering of information cues has been discussed to some extent in the literature. No specific decision model based on ordered cues has been proposed. The integration of information is described by the weight attributed to each information element and the way in which the information elements are summed. This summation process is referred to as cognitive style.

Tversky and Kahneman (1973) and Einhorn and Hogarth (1981) have identified several factors affecting the weight assigned to elements of information (Ungson and Braunstein, 1982):

1. Accessibility to information in the environment.

2. The way in which information is stored and reaccessed in the brain.

3. Stored information is affected by:

    a. emotional relevance,
    b. specificity, and
    c. temporal ordering.

4. Information is enhanced by the individual's ability to generate associative networks and rehearsals.

March and Simon (1982) discuss the implication of order and orderliness in organizational settings. They propose that decision making depends on an ecology of attention where the elements of the distribution of attention are exogenous to the decision process.

Hammond, McClelland and Mumpower (1980) discuss the effects of order as time dependent. That is, the most recent information is weighted highest. In addition they point out that the requirement to rank order alternatives versus assigning a rating generates different decision models.

These observations refer to ordering effects as external to the decision model and as such are not the same phenomenon as the rank ordering of decision cues proposed by this research. The only decision model which even hints at ordering of information cues is the Integration Theory model proposed by Anderson (1971,1972).

Integration theory is similar to the regression approach except that information need not be utilized in an additive manner. Integration theory is a general purpose approach which supports several algebraic decision models. One model, referred to as the averaging model (Kaplan and Schwartz, 1977), is given as:

$$R_s = w X + (1 - w)Y \tag{5}$$

where the response R_s is a function of the average information on cue X and Y. The weights sum to one. This requirement results in a weighted average effect. While rank ordering of information by weight is not stipulated, such a formulation is certainly possible.

Although numerous researchers (Ungson and Braunstein, 1982; Kaplan and Swartz, 1977 and 1975; Hammond, McClelland and Mumpower, 1980) have discussed the general nature of ordered information cues and the possible sequential nature of processing in the brain, no decision model has been formulated which directly attacks this problem. This research does propose to address the sequential processing of information and, therefore, provides insight into this alternative cognitive style.

CHAPTER III

RESEARCH METHODOLOGY

This chapter presents the research methodology. First a general summary of the research effort is discussed. The proposed decision model is developed and the experimental design is discussed. In particular, the methodology for testing the hypotheses is described.

Overview

A technique called policy capturing was used to provide an experimental test for individual decision making. Two groups of decision makers were asked to complete a decision making exercise based on a fractional replicate of a 2^n experimental design in the case of the soybean production exercise and a 3^n design in the case of the job selection exercise. The number of experimental factors, that is decision cues, was established in advance by careful discussions with experienced decision makers.

Six weighting schemes were used to model the decision making process. Subjective weights were weights supplied by the decision maker. Weights were estimated by statistical means and included relative weights derived from linear regression, decision weights derived from restricted least squares estimation, and nonlinear weights derived from nonlinear least squares estimation. Equal weights refer to cues equally weighted and ordered by relative weight while subjectively rank ordered cues are equally weighted but ordered by subjective weight.

Each decision model was used to predict the decision of each decision maker with each of the six weighting schemes. The sub-groups of the original decision maker sample such as demographic or functionally unique decision makers were compared to determine decision model differences. A statistical analysis was completed to determine if there were significant differences between the alternative weights across the entire sample. The nonlinear weights were dependent on the order that the decision factors were brought into the decision model and as such were not directly comparable to the other weights.

Comparisons of decision model and factor weight performance was analyzed using analysis of variance techniques. The experimental design was a 2 x 6 factorial experiment with a randomized block design. The two models form one set of treatments and the six weights form the second treatment. The interactive effects were investigated since it was expected that model-weight interaction would be highly significant. Comparison of treatment effects was completed using statistical analysis of the appropriate contrasts formed after the preliminary ANOVA was completed. That is, contrasts were not specified a priori.

A proposed decision model (presented in the next section) was developed and mathematically derived. This model used the estimated weights from the previous steps and was used to predict individual decisions. Estimates of the proposed nonlinear model weights were derived using the nonlinear regression procedure NLIN in SAS. The model's explanatory power, as measured by squared bivariate correlation of predicted decisions with actual decisions and by mean square error of prediction was computed and compared with the explanatory power of the linear model.

Each set of weights was used with each decision model to generate predicted decisions. These predictions were correlated with the actual decisions to form the first ANOVA response variable. The mean squared error of the predicted decision versus the actual decision was the second ANOVA response variable. These response variables measure slightly different performance metrics in that correlation implies no cause and effect relationship. The measurement of mean square error on the other hand is a measure of the effectiveness of the estimation technique and implies a statistical model.

Proposed Compensatory Decision Model

Consider that for any given scale or standardization of the decision cues (factors in the exercise experimental design), the final adjusted rating for any alternative is the sum of weights times their respective factor scores. Another way to view this process is to realize that the final rating is an indicator of how far from perfection a given alternative is given a set of weights and scores. In fact, the rating could be obtained by simply accumulating the deviation from a perfect rating as each factor-weight is brought into the model. The same numerical rating would be obtained. However this process of accumulating deviations from perfection implies sequential processing of factors and will yield a decay curve which depicts the reduction in the rating for each factor-weight combination. The decayed rating curve will terminate at the same rating obtained by applying the traditional linear model.

The accumulated deviation concept or the decayed rating is easily obtained by assuming the alternative is initially considered to be perfect, that is, it is assigned an initial rating of the highest value of the selected cue scores. The decayed rating is obtained by subtracting the deviation from a perfect score times the factor weight from the preceding rating. Mathematically, using a slightly different notation to distinguish the models:

$$R_i = R_{i-1} - W_i \times (\text{Max}(S) - S_i) \tag{6}$$

where

R_i = the decision (rating),

W_i = the cue weight,

S_i = the score for cue i,

Max(S) = the maximum score possible,

R_0 = the initial rating = Max(S).

This function is a real valued, monotonically decreasing function which terminates at the exact rating (Y_i) of the linear compensatory model given the same set of weights.

Note that this model implies a decision process similar to a jury trial. That is, the alternative is assumed perfect (not guilty) until proven otherwise by accumulated evidence. This evidence is weighted in some manner. Furthermore, the decision maker (judge) has some threshold of acceptability which, if reached, makes the alternative unacceptable (guilty). Note the similarity of this logic to the basic assumptions of statistical hypotheses testing!

The advantages of the proposed model are clear when the decaying rating is plotted against the factors. It seems reasonable to order the factors (decision cues) in the order of weight from high to low. Although the decision model does not require this, it is suggested so that the model can be consistently formulated and since it is intuitively appealing. Note also that a worst case rating can be obtained by considering an alternative whose cues (decision criteria) are set at the minimum score possible. If the proposed model is then used to generate a worst case rating, then a worst case decayed rating is also generated which is dependent solely on the factor weights. Figure 2 depicts a decision making situation with 10 criteria and unequal weights. Note the progression from a perfect horizontal line at the perfect score of 5 to the final rating of slightly over 3. The worst case rating is also shown.

At this juncture recognize that the traditional compensatory model estimates a point statistic interpreted as a decision rating. It does not distinguish the order of the factor-weight combinations. The proposed model has increased the dimensionality of the decision making process to 2 dimensions, an area comparison versus a point. A simple extension of the proposed model to include two-way interactions adds a third dimension (depth) to describe a decision making process which is modeled as a volumetric comparison! The fact that interactive effects are rarely found significant could be explained in terms of the human brain's limitation in perceiving three dimensional objects. The brain can easily discriminate between geometric figures with different areas. However, it is much more difficult to distinguish volume differences.

Note that any alternative estimated by the proposed method must generate a decayed rating curve which falls between the perfect horizontal maximal score and the worst case rating. A direct comparison of the area of the perfect alternative versus the area subtended by the alternative in question given a worst case area is easily obtained. At

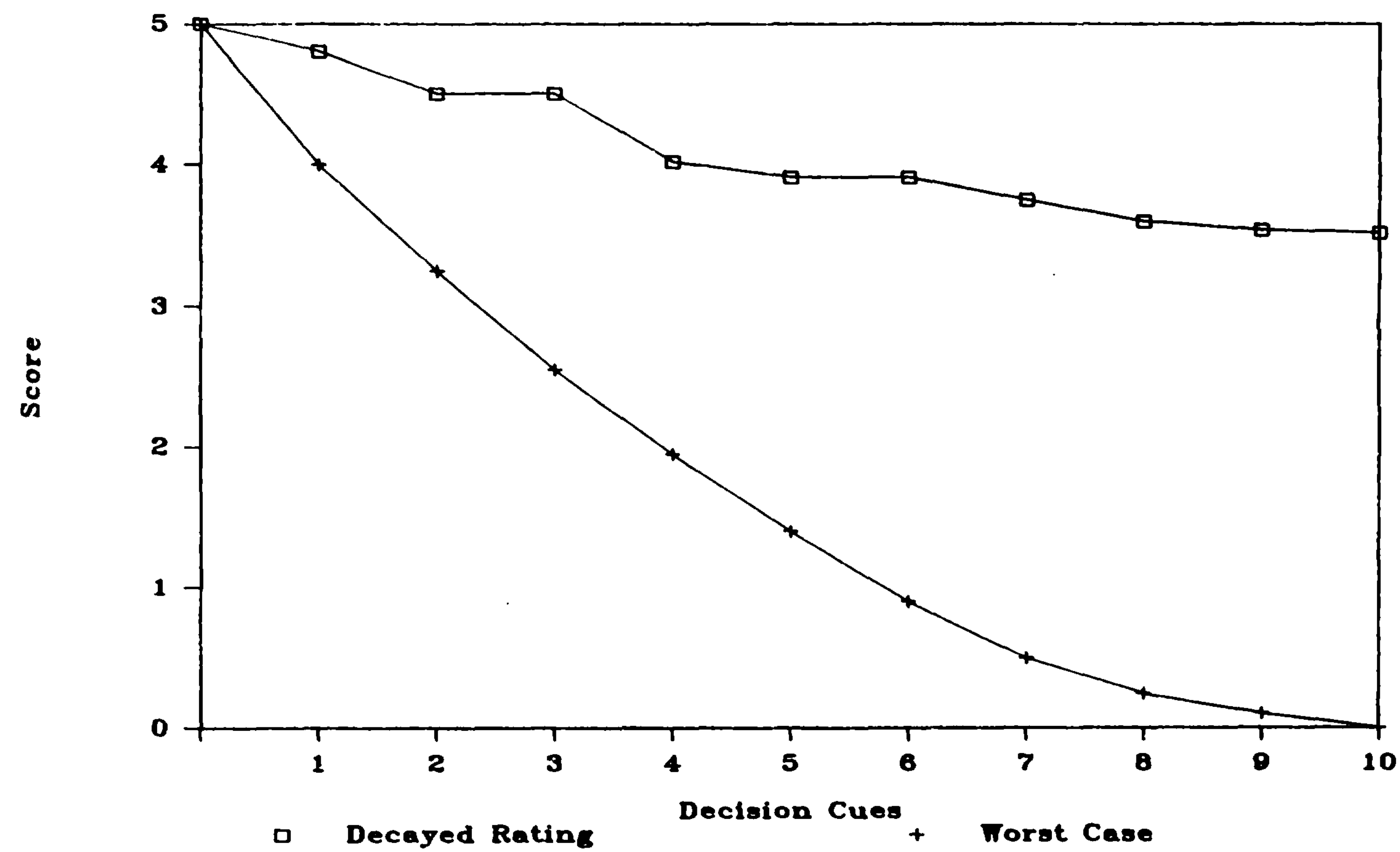

Figure 2. Proposed Scoring Rule

this point recognize that an area is an integration process. That is, the area encompassed by the decayed rating is the integral of the accumulated factor-weight combinations. Furthermore, multiple alternatives can be scored by this method and plotted together to produce an extremely visual comparison of alternatives. The critical difference in the models is that the proposed model is concerned with the progression of the decision not just the final rating.

Figures 3 and 4 are tabular comparisons of two alternatives scored by the traditional linear additive model and by the proposed method. Note that the traditional method rates the alternatives equally (gives the same rating). However the proposed model yields substantially different ratings. Figure 5 is a plot of both alternatives. The difference is easily visualized. Case 1 alternative consistently outperforms Case 2 alternative on the highly weighted factors. Clearly, different decisions are reached by the proposed and traditional models. The question is which model has better explanatory power or is viewed as more accurate by the decision maker?

The graphical depiction of the rating decay can be used to motivate the computation of the proposed model rating. A mathematical model follows.

When the proposed model is composed of only the main effects of the cues, that is, no interactions, the decayed rating curve has been shown to be a two dimensional graph. The rating can be interpreted in terms of the area represented by the particular set of factor-weight combinations. That is, the decayed rating is unique for each set of weights and factor scores and generates an area dependent on the weights and scores. This area can be divided by the area of a perfect alternative

Figure 3: Case 1, High Scores on Highly Weighted Factors

Maximum score is: 5.00

Factor	Score	Weight	S x Wt	Decay	Worst
				5.00	5.00
Factor 1	4.00	0.25	1.00	4.75	3.75
Factor 2	5.00	0.17	0.85	4.75	2.90
Factor 3	5.00	0.12	0.60	4.75	2.30
Factor 4	3.00	0.10	0.30	4.55	1.80
Factor 5	4.00	0.10	0.40	4.45	1.30
Factor 6	4.00	0.08	0.32	4.37	0.90
Factor 7	2.00	0.06	0.12	4.19	0.60
Factor 8	3.00	0.05	0.15	4.09	0.35
Factor 9	4.00	0.05	0.20	4.04	0.10
Factor 10	3.00	0.02	0.06	4.00	.00
Totals	37.00	1.00	4.00	43.94	14.00
Means	3.70	0.10	0.40	4.45	1.73
Variances	0.8100	0.0041	0.0915	0.1052	2.3797

Traditional Rating is 0.8000, that is 4.00 ÷ 5.00

Proposed Rating is 0.8317, that is (43.94 - 14.00) ÷ (50 - 14.00)

Percent Difference is 3.96%

Figure 4: Case 2, Low Scores on Highly Weighted Factors

Maximum score is: 5.00

Factor	Score	Weight	S x Wt	Decay	Worst
				5.00	5.00
Factor 1	3.00	0.25	0.75	4.50	3.75
Factor 2	3.00	0.17	0.51	4.16	2.90
Factor 3	4.00	0.12	0.48	4.04	2.30
Factor 4	5.00	0.10	0.50	4.04	1.80
Factor 5	5.00	0.10	0.50	4.04	1.30
Factor 6	5.00	0.08	0.40	4.04	0.90
Factor 7	5.00	0.06	0.30	4.04	0.60
Factor 8	5.00	0.05	0.25	4.04	0.35
Factor 9	5.00	0.05	0.25	4.04	0.10
Factor 10	3.00	0.02	0.06	4.00	.00
Totals	43.00	1.00	4.00	40.94	14.00
Means	4.30	0.10	0.40	4.18	1.73
Variances	0.8100	0.0041	0.0332	0.0859	2.3797

Traditional Rating is 0.8000, that is 4.00 ÷ 5.00

Proposed Rating is 0.7483, that is (40.94 - 14.00) ÷ (50 - 14.00)

Percent Difference is -6.46%

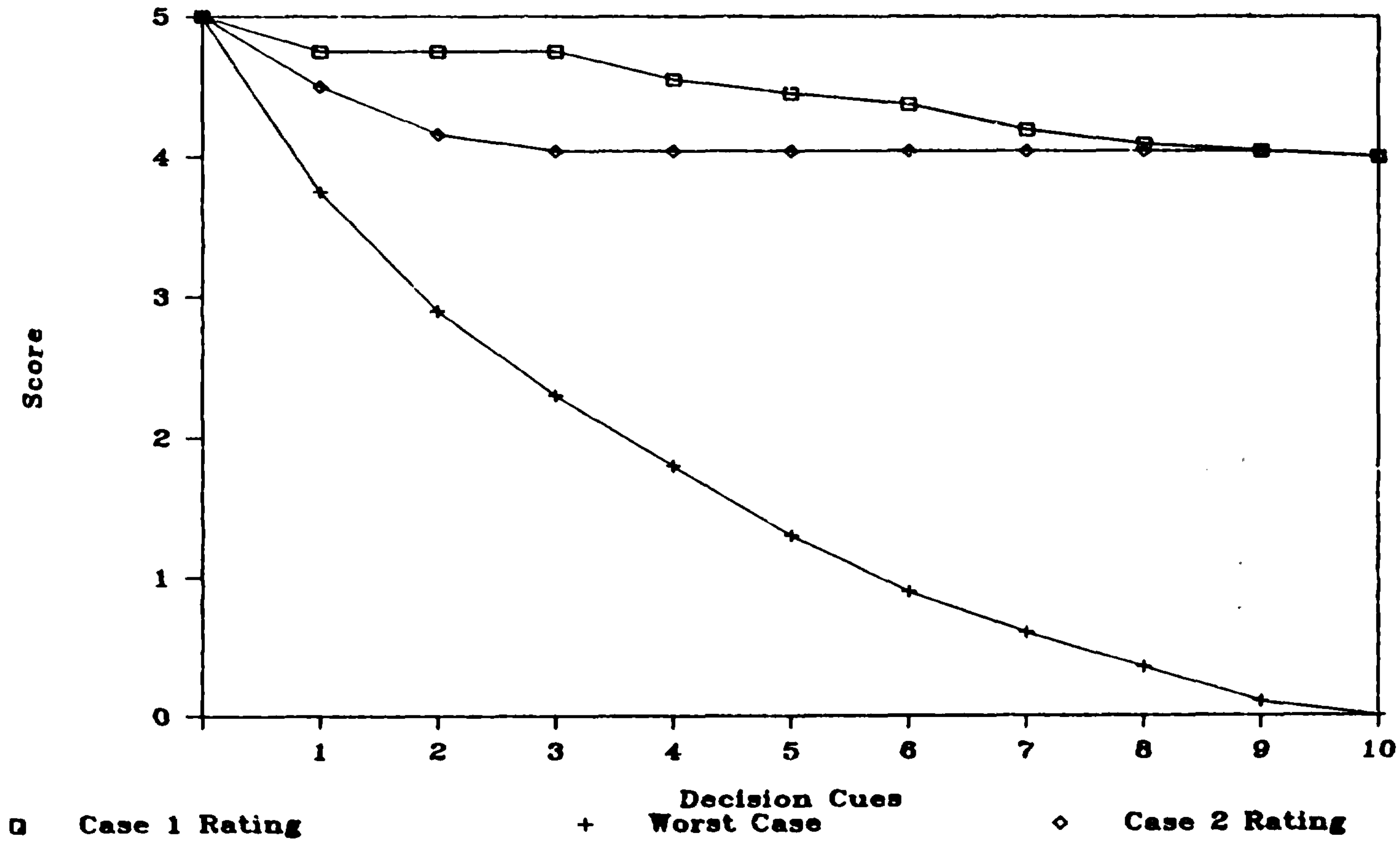

Figure 5. Comparison of Cases 1 and 2

to yield a relative rating usable to compare alternatives. In addition, the worst case decayed rating places a lower bound on the area an alternative can generate. Therefore the worst case area can be subtracted out of the perfect area and the alternative's area before the ratio is taken. This step normalizes the rating to be a relative rating of an alternative versus perfection given a worst case lower bound.

If interactive effects are introduced then the dimensionality of the model increases. For example, if two-way interactions are included a three dimensional model is formed and ratings are based on comparisons of volumes. The findings of previous research have demonstrated the low explanatory power of two-way interactions and all but non-existent effect of higher order interactions. This fact seems particularly significant since the decision maker exists in a three dimensional world where comparison of volumes is much more difficult than areas.

Mathematical Model

The mathematical derivation follows easily from the original proposed model equation and the graphical interpretation. The main effects proposed model is presented here although the interactive effects model can be readily derived. Note that areas are computed by taking integrals:

$$\text{Area of Decayed Curve} = \int_0^N R \, d_i \tag{7}$$

where

$$R_i = R_{i-1} - W_i \times (\text{Max}(S) - S_i) \quad . \tag{8}$$

In this model the integration can be replaced by finite summations since the areas are defined across unit sized cues. That is:

$$\text{Area of Decayed Curve} = \sum_{i=1}^{N} (R_{i-i} - W_i(\text{Max}(S) - S_i)) \quad . \tag{9}$$

Combining this equation with the use of a calculated ratio of the alternative's area to a perfect alternative given a worst case decayed curve yields the proposed model:

$$R_j^* = \frac{\sum_{i=1}^{N}(R_{i-1} - W_i(\text{Max}(S) - S_i)) - \sum_{i=1}^{N}(R_{i-1} - W_i(\text{Max}(S))}{N\ \text{Max}(S) - \sum_{i=1}^{N}(R'_{i-1} - W_i(\text{Max}(S))} \tag{10}$$

where

R_j = the proposed model's decision (rating),

W_i = the relative cue weight for cue i,

N = the number of cues,

S_i = the standardized score for cue i,

R'_i = the worst case rating,

$\text{Max}(S)$ = the maximum standardized score,

$R_0 = R'_0$ is set to Max(S).

Policy Capturing Instrument

Policy capturing instruments were used to provide a database of orthogonal factor combinations and decision maker responses. The instrument was a simulated decision making exercise designed as a 2^n factorial experiment for the soybean production exercise and a 3^n factorial experiment for the job selection exercise. Decision criteria were determined by literature reviews of similar research and by detailed discussions with decision makers experienced with the decision being studied. Copies of the decision making exercises are included in the Appendices.

The job selection exercise was a previously developed experiment and has been used in other research. The cues include salary level, promotion potential and geographic location. Students were asked to view 27 alternative job descriptions where each cue is set to one of three levels. The participant was asked to rate each alternative in terms of their interest in that job.

The soybean production exercise was coordinated with the South Carolina Farm Bureau. The decision factors included use of resources, degree of government support, anticipated sales price, anticipated market, anticipated yield and availability of money. Each factor took on one of two levels. These cues were carefully discussed with experienced farm managers and with the executive board of the Farm Bureau. Pre-tests were completed to insure the orthogonality of the design and to check for semantic errors.

In the case of the job selection exercise, students at Clemson University voluntarily completed the simulation. No demographic differences between students were investigated.

In the case of the soybean production exercise, the randomly selected participants were mailed the packet of instructions and alternative crop descriptions. Farmers were asked to record their responses and return the exercise for analysis. Each participant received the estimated relative weights for his model and the state averages.

The farmers were asked to describe themselves in various ways based on the interest of the Farm Bureau. Farmers were described by size of the farm, dollar sales level, experience level, age, education, full or part-time, whether or not vocational agricultural training was received, and whether or not post high school education was in an agricultural discipline.

Soybean farmers were sampled using the membership database of the South Carolina Farm Bureau. Five hundred members were drawn at random and checked to determine if they actively produce soybeans on their farms. Of the 500, 302 were mailed the decision making instrument. Thus, a rich cross-section of farmers was sampled who varied in each demographic description. Table 1 presents the sample description. The entire state was sampled to remove any regional effects. The two attributes shared by the participants were the production of soybeans on their farm and membership in the Farm Bureau.

Policy Capturing Experiment Design

Since it was desired to maintain as small as possible exercise, a fractional replicate was utilized for the soybean production exercise. A fractional replicate is based on using the highest order interaction as the defining contrast. Aliases were checked and pooled with error. The design consisted of the use of one block where the experimental units were orthogonal. In the case of the soybean exercise the design was a one-half replicate of a 2 to the 6 design. The design for the job selection exercise was a 3 to the 3 full replicate. In the soybean production exercise the interactions were used as the error term.

Data Collection and Recording

Decision making exercises were mailed to the decision making group. The decision makers were soybean producers in South Carolina. Soybeans

Table 1. Description of the Soybean Exercise Participants

Sample Demographic Description	No.	% of Sample
Number of Acres of Soybeans		
100 or less acres	7	19.44%
101 - 250 acres	10	27.78%
250 - 500 acres	11	30.56%
Over 500 acres	8	22.22%
Sales of all Farm Products		
More than $100,000 per year	15	41.67%
Less than $100,000 per year	21	58.33%
Full or Part-time Farmer		
More than 50% of net income from farm	24	66.67%
Less than 50% of net income from farm	12	33.33%
Farm Experience		
More than 15 years	23	63.89%
Less than 15 years	13	36.11%
Age		
More than 35 years old	24	66.67%
Less than 35 years old	12	33.33%
Education		
No formal school graduate	2	5.56%
High school graduate	11	30.56%
TEC school graduate	1	2.78%
2 year college graduate	4	11.11%
4 year college graduate	14	38.89%
Advanced or Professional graduate	4	11.11%
Vocational Agricultural Training in High School?		
Yes	20	55.56%
No	16	44.44%
Was post high school education agricultural?		
Yes	12	52.17%
No	11	47.83%

are the highest dollar value crop in the state and the production decision represents a complex and risky venture. The Farm Bureau membership was first screened for registered soybean producers. Of the more than 11,000 soybean farmers recorded, 500 were randomly selected by computer. These 500 were contacted individually to ascertain that they in fact currently produce soybeans on their farm operation. Of the sample, 302 were selected and constitute the participants in the decision making exercise.

The students used in the job selection exercise were juniors and seniors in an introductory management course.

The individual responses were recorded on computer records with an identification number, demographic/functional information, and the exercise data. Each individual model was estimated as well as composite models by demographic group or function.

The beta coefficients were estimated by regression techniques and the relative weights calculated. In addition the individual supplied his own set of subjective weights as part of the exercise and were used in testing the lack of insight hypothesis.

Nonlinear weights as well as restricted least squares weights were also estimated and recorded by decision maker.

The decision predictions by both models for each set of weights were recorded. The mean square error and squared bivariate correlation was computed and recorded by each decision maker for each model and set of weights. This resulted in 12 observations of the two response variables per decision maker.

Estimation of Relative Weight

Relative weights (RW) were determined by first estimating a linear multivariate model where the participants response was taken as the dependent variable and the cue levels as the independent variables. Use of Equation (3) allowed computation of each cues' relative weight (RW) for each decision maker.

The multiple coefficient of determination, R^2, was used as a measure of consistency and as a measure of the power of the linear compensatory decision model.

Estimation of Decision Weights

Decision weights (DW) were estimated by restricting the linear estimation technique to force the regression coefficients to sum to one. Mathematically

$$Y = B_0 + B_1X_1 + B_2X_2 + \ldots + B_NX_N + \text{Error}$$

$$\text{Subject to: } B_1 + B_2 + \ldots + B_N = 1 \,. \tag{11}$$

In order for this formulation to make sense the decision cue information must contribute to the decision in a positive manner. Otherwise the weights would sum to one but some weights may be negative. The intent of this formulation was to estimate the actual weight placed on information cues as the decision was made. Note that the estimate of relative weights is a nonlinear transformation of the beta weights which are themselves standardized weights. Relative weights measure the contribution of a cue to the explanatory power of the particular decision maker's linear regression model. Decision weights measure the actual importance of the cue in the decision making process.

The use of a forced restriction on estimation results in biased estimators if the restriction is not in fact valid. However, the objective here was not to study the structure of the regression model. The objective was to determine weights which sum to one regardless of the appropriateness of the restriction.

The decision making exercises were worded so that information cues contribute in the positive direction. This requirement was consistent with the general nature of policy capturing. Decision weights were estimated using the REG procedure in SAS with the restriction enforced.

Finally it was important to note that restricted least squares estimation renders the conventional interpretation of R^2 invalid. That is, direct comparison of linear versus restricted linear model R^2 was exceedingly dangerous, if not undefined.

Estimation of Nonlinear Weights

The estimation of nonlinear weights (NW) was dependent on the ability to formulate the nonlinear objective function in such a way as to make possible either direct search algorithms or search algorithms based on knowledge of objective function derivatives. The formulation of the sequential judgment model in equation 10 only lends itself to direct search.

The nonlinear model was reformulated by algebraic manipulations which result in a much more tractable objective function. This formulation has the desirable property of being differentiable. That is, derivatives with respect to the cues can be computed. This fact allowed the more powerful gradient based nonlinear optimization techniques to be employed.

In general the nonlinear estimation problem is:

$$Y = F(B_0, B_1, \ldots, B_N) + e \tag{12}$$

where the normal equations become:

$$X'F(B) = X'Y \tag{13}$$

where

$$X = dF/dB \quad . \tag{14}$$

The estimation process begins at some specified starting point B_0. The objective was to compute new values of B which reduced the sum of squared error. Mathematically:

$$SSE(B_0 + \Delta) < SSE(B_0) \quad , \tag{15}$$

where SSE is the Sum of Squared Error.

The primary concern was the determination of Δ. Many methods exist. After several trial runs it was determined that Marquardt's method (Marquardt, 1963) performed best of the alternatives attempted. The method was able to converge to a solution with usually less than five iterations.

Marquardt's updating formula is:

$$\Delta = (X'X + \lambda I)^{-1} \quad (X'Y) \quad . \tag{16}$$

Note that both a direction and distance are specified. Other methods were also able to achieve convergence to a solution but at considerably more computer time. Marquardt's method is available in the NLIN procedure of SAS.

An important aspect of the nonlinear weight estimation procedure was to recognize that the solution space was well defined, but that the optimal solution was a function of the relative values of the cue weights, not the absolute values. This fact was best observed by starting the procedure at many initial vectors of cue weights. The algorithm terminated at weights which had identical asymptotic properties but very different absolute values.

This problem was overcome by noting that the sequential nature of the nonlinear model effects the estimation process itself! The temporary selection of a previous weight affected the derivatives for each succeeding weight, thereby guiding the algorithm to a solution which was optimal for the starting point selected. However, if any given solution was standardized by establishing any cue weight and calculating the others in terms of the relative values of the optimal weights, it was found that the same weights result for any starting point.

Since it was desired that the weights sum to one all that was required was that some start point be selected and the resulting optimal solution be converted to a standard score where the weights sum to one. Clearly the order in which the cues were brought into the nonlinear model affected this process. Therefore, all nonlinear models were estimated with the cues included in the same order.

The derivation of the reduced nonlinear model and its derivative are included in the Appendices as well as the SAS code required to estimate the nonlinear weights.

Subjective Weights

Subjective weights were simply those weights given by the decision maker. These weights represent how much importance the participant believes is placed on the cues. The research objective with regard to subjective weights was twofold. First, did the weights perform well in either decision model? Second, was there a difference between the subjective weights and those weights which were estimated via statistical techniques? This second objective is the so-called "lack of insight" hypothesis and reflects the concern that human decision makers do not know the underlying importance of information and hence need decision models.

Equal Weights

Equal weights required no estimation or requests of the decision maker. The cues were simply given equal weights which sum to one. In the linear model case it made no difference which order equally weighted factors were included in the model. However the nonlinear model was extremely sensitive to order effects.

Two possibilities arose. The equally weighted factors could be brought into the sequential model based on the subjective weight order. This would imply that a decision maker may not estimate the weights well but may rank order the cues better. The other alternative was to bring the cues into the model in the order of known importance. That is, estimate the decision or relative weights and bring the cues into the nonlinear model in the order specified by the magnitude of these weights. Note that both relative weights and decision weights always rank order the cues the same way, albeit with very different weights.

Both of these possibilities were investigated. The equal weights implemented in relative weight order were simply referred to as equal weights (EW). These weights represented the best performance possible with equal weights in the nonlinear model since the proper order is known.

The use of equal weights in subjective weight order was referred to as subjectively ranked (SR) weights. Another measure of "lack of insight" was the difference in performance of the sequential model when these two weighting schemes were compared.

Analysis of Variance Experiment Design

Armed with estimated weights and two alternative decision models it remained to analyze the performance of the model-weight combinations. This was best accomplished using a factorial experiment with a randomized block design with two levels of the model treatment and six levels of the weight treatment. The model treatment consisted of the linear compensatory model and the proposed, sequential decision model. The six weights included the decision weights, equal weights, nonlinear weights, relative weights, subjective weights, and the subjectively ranked equal weights. The model-weight interaction was included since it was expected that significant decision model-decision weight interaction would be present.

The variability due to individuals was removed from real error by using decision makers as blocks. The number of decision makers sampled provided the necessary replications per cell. All that remained was the choice of the response variable. Two response variables were measured.

Mean Squared Error Response Variable

The mean squared error was measured as the squared difference between the predicted decision of each model and weight to the actual decision. These squared errors were average for each decision maker and recorded as a response variable.

The mean squared error response was an overall indicator of the performance of a decision model and set of weights. The objective of the research was to determine if there were differences between the non-linear and linear model across weights and between the weights within models. These paired comparisons were done using Tukey tests which allow the experimenter to specify the experiment-wise error rate.

Squared Bivariate Correlation Response Variable

A second response variable was computed which measures the degree to which the predicted decisions vary with the actual decisions. This approach made no statistical assumption on the nature of the relationship. The simple correlation between predictions and actual decisions was computed and squared to yield the coefficient of determination.

It was tempting to use the R-square of the regression model for this purpose. However the computational version of the R-square provided by restricted least squares estimation and nonlinear estimation were not directly comparable with the unrestricted linear model. Furthermore, the use of subjective and equally weighted cue models did not generate a coefficient of multiple determination. While complex adjustments to R-square exist which purport to make comparisons possible, it was felt that a more straightforward and conservative approach should be taken.

The computation of the correlation was direct and subject to no interpretation problems regardless of the method used to predict decisions. The meaning of a correlation or coefficient of determination was well established and yields slightly different insight than the mean square error measurement. While the mean square error was a better overall performance index, the squared correlation index was a measure of how well the models tend to work in relation to the actual decision making behavior.

One issue regarding the squared correlation statistic is noteworthy. Since a correlation must fall between -1 and 1 the squared values must fall between 0 and 1. Clearly the assumption of a normal distribution of squared correlation statistics is suspect.

Certainly the population of decision makers had some average correlation between predicted and actual decisions. This average also must possess some variability. The fact that individual correlations were restricted to lie in a known range does not preclude the discussion of the distribution of the sample correlations. Furthermore, a fixed effect analysis of variance is not sensitive to the distribution of the response variable. The F test used to determine the presence of a treatment effect is an extremely robust statistic.

Snedecor and Cochran (1967) have derived the sampling distribution of the correlation statistic and conclude that the skewness of the distribution is a direct function of the sample size and the population correlation. As the sample sizes get larger the distribution never becomes normal but approaches a quasi-normal shape. Application of the Central Limit Theorem justified the use of bivariate correlation measures in that the sampling distribution of the average correlation is approximately normal regardless of any skewness of the underlying distribution of individual statistics.

The primary concern in the fixed effects ANOVA model is the nature of the error distribution. The fact that individual observations were known to fall in a fixed range did not detract from the ability of the ANOVA procedure to measure an overall treatment effect for the same reason that the normal model can be used to describe the distribution of peoples' height even though the selection of a variance must include the positive probability of negative height!

Tests of Hypotheses

Based on the experimental design and data collection, each hypothesis presented in the introduction was tested.

The explanatory power of the traditional compensatory model was determined by F tests and examination of R-square. The effects of two-way interaction were examined by reformulating the model and estimating new beta weights. T tests were used to determine the significance of interactive effects. Based on these tests a linear compensatory decision model was formulated and used to estimate each experimental unit decision.

To test the lack of insight hypothesis, paired t tests were completed for each cue weight except for the nonlinear weights. Paired t tests were used to determine if significant differences exist between what a decision maker does and what he thinks he does.

The comparison of demographic/functional group models was completed by comparing the linear regression models. Each sub-sample model was estimated separately as well as the composite model for all decision makers. Differences between groups was determined by Chow's F test (Chow, 1960).

Differences in decision model performance across weights were determined based on the results of the analysis of variance. Significant interaction effects would mean that pair-wise comparisons across models and weights must be completed.

The average performance of the alternative decision models was computed by evaluating contrast across all six weights for each decision model. A Bonferroni comparison (see Neter and Wasserman, 1974) was used to obtain sensitive experiment-wise confidence levels. Contrasts were not established in advance since the complex nature of the comparisons could not be predicted. Rather, the comparisons were completed based on the results of the analysis of variance findings.

Comparisons and contrasts were completed for both response variables and for both decision exercises. Conclusions were discussed based on the aggregate statistical findings.

In addition, illustrative examples of the sequential method are included. These problems are taken from current literature and formulated as sequential decision models. Results are compared to the author's suggested solutions.

CHAPTER IV

RESULTS

This chapter presents the results of two decision making exercises where two decision models and six sets of weights are incorporated into separate 2 x 6 factorial experiments. The mean square error of prediction and the squared bivariate correlation of predicted versus actual decisions are the measured response variables. Analysis of variance is used to determine the effect of model, weight and model-weight interaction on the response variables. Appropriate contrasts are computed and paired t tests are presented. The average performance of the linear versus the nonlinear decision model is compared. Chow's F tests are used to determine if significantly different decision models exist between demographic groups within the soybean production exercise.

Overview

Two different decision making exercises were used to model the decisions of distinct groups of decision makers. The first group consisted of farmers in the state of South Carolina who currently produce soybeans for profit on their farms. Each decision maker was asked to indicate his willingness to increse or decrease production plans given information on six environmental factors. The decision maker was presented with 32 alternatives where each factor takes on one of two levels. The responses were recorded and used to estimate relative, decision and nonlinear factor weights.

The second experiment was intended to add validity to the research by analyzing the responses of students to a job selection exercise. Twenty-seven jobs were presented to the decision maker which were described by three factors which take on one of three levels. Again, responses were recorded and used to estimate relative, decision and nonlinear weights.

Each decision maker in both experiments was asked to estimate the importance placed on each factor. These estimates were recorded as subjective weights and then used to rank order the factors into subjectively ranked factors with equal weight. Finally each factor was again equally weighted but ranked in order of relative weight. These weights represent the upper bound on performance for equally ranked factors since the proper rank order was known.

Each set of weights was checked to make certain that they sum to one. This requirement was consistent with the formulation of the nonlinear, sequentially based decision hypothesis. Each set of weights was used to predict decisions for each experimental unit of the original experiment. These predictions generated an error which was squared and averaged to produce a mean square error response variable. Also the predictions were correlated with the actual decisions to compute Pearson correlation statistics per decision maker per type of weight per model.

Paired t tests between each set of weights were completed to determine if significant differences exist. Nonlinear weights were excluded from this analysis since the nonlinear weight is dependent on the order the factors were brought into the model.

The analysis of variance for each experiment was conducted to determine if treatment effects were present when decision makers were used as blocks. Tukey comparisons were used to test paired contrasts across the linear versus the nonlinear model and within each model across weights.

The primary purpose of the job selection exercise was to provide validity to conclusions obtained through analysis of variance. This experiment used fewer factors but the factors are set at more levels. It was expected that differences in decision model performance would be attributable to the nature of the decision making exercise design.

In summary, two 2 x 6 factorial experiments were conducted with 36 and 21 replications per cell. Predicted decisions were used to compute two response variables, mean square error and bivariate correlation. Analysis of variance was used to determine the various treatment effects and contrasts were evaluated. Table 2 depicts the experimental design.

Soybean Production Decision Making Exercise

A decision making exercise (Appendix A) was completed and extensively discussed with the executive board of the South Carolina farm Bureau. Farm Bureau interest also included a desire to compare decision making behavior among various demographic groups. Farmers were grouped by age, experience, yearly sales, farm size, education, full or part-time, and whether or not vocational agricultural training was received in high school.

A pre-test was used to check vocabulary and to determine if the exercise was well understood. Based on the pre-test minor corrections

Table 2. Experimental Design and Replications Per Cell

	Soybean Production Exercise				Job Selection Exercise			
	Linear Model		Nonlinear Model		Linear Model		Nonlinear Model	
Weights	MSE	r^2	MSE	r^2	MSE	r^2	MSE	r^2
Equal	36	36	36	36	21	21	21	21
Decision	36	36	36	36	21	21	21	21
Nonlinear	36	36	36	36	21	21	21	21
Relative	36	36	36	36	21	21	21	21
Subjective	36	36	36	36	21	21	21	21
Subjective Ranked	36	36	36	36	21	21	21	21

NOTES:

1. Equal weights are weights which are identical and sum to one. In the nonlinear model the cues are brought in in relative weight order.

2. Decision weights are obtained by estimating a restricted linear model to force the weights to sum to one.

3. Nonlinear weights are obtained by direct estimation of the sequential decision model using nonlinear optimization. The actual weight is dependent upon the order in which the cues are brought into the model.

4. Relative weights are derived from unrestricted regression and computation of beta weights.

5. Subjective weights are those weights supplied by the decision maker.

6. Subjectively ranked weights are equal weights but the cues are entered in the nonlinear model in the order of subjective weights.

to wording were completed. The pre-test average R^2 for the linear compensatory model was 0.739.

Using the South Carolina Farm Bureau membership database, 500 members were drawn at random. Of these, 302 were determined to be involved in soybean production. Each of the 302 was mailed the exercise and instructions. Fifty-two responses were received for a response rate of 17%. However, some requested they not be sampled while others failed to complete the exercise correctly. Thirty-six usable samples were obtained. Each sample contained 32 decisions which resulted in 1152 observations.

The first step in the analysis checked for interactive effects in a linear decision model. When all observations were pooled and a single regression model estimated, no significant interactions at alpha = 0.05 were found. Among individual decision makers, 5 models exhibited one interactive element, 6 models contained two significant interactions, and 2 models contained 3 or more interactions significant at alpha = 0.05.

No pattern or common interaction among the significant ones was apparent. The group R^2 for the interactive model was 0.545 versus 0.5045 for the main effects model. This slight improvement in explanatory power coupled with the random, infrequent nature of the interactive terms supports the rejection of the interactive model. Therefore the research is based on the six main effects.

The average individual R^2 of the linear regression model was used to determine the internal consistency of the decision makers. The linear model, having been demonstrated as a robust model of human decision making, generated an average R^2 of 0.792 for the soybean exercise.

Every linear model was computed to be statistically significant at alpha = 0.05. It was concluded that the decision makers made highly consistent decisions which were modeled very well by a linear formulation.

Each decision maker's linear model was estimated to compute the beta weights and R^2 which was used to compute the relative weight for each factor (RW). Each model was reestimated including a linear restriction that the weights sum to one to yield least squares estimates of decision weight (DW). Each decision maker's responses were used to estimate the nonlinear weights (NW) via Marquardt's Method (1963) of nonlinear least squares. Finally subjective weights (SW) and equal weights (EW) were recorded.

Table 3 presents the average weights for each of the six factors. Note that nonlinear weights depend on the order in which the factors are brought into the model and, therefore, should not be compared directly with other weights. Rather, a comparison of nonlinear weight performance versus other weights was completed via analysis of variance techniques.

Paired sample t tests were used to compare equal, subjective, decision and relative weights for each decision factor. Table 4 presents t values for each paired test and depicts whether or not the statistic was significant. Since the t tests were intended to determine the equality of the weight and not the direction of the difference, absolute value t statistics are shown. Note that significant differences were generally obtained except that fewer differences occur between decision weights and subjective weights.

To determine differences in decision models across demographic groups, the Chow F test was used. Error sum of squares for each

Table 3. Comparison of Average Individual Cue Weights for the Soybean Exercise (N = 36)

Weight	Sales Price	Expected Yield	Use of Resources	Anticipated Market	Degree of Government Support	Availability of Money
Equal Weight	0.167	0.167	0.167	0.167	0.167	0.167
Relative Weight	0.361	0.322	0.147	0.071	0.056	0.047
Decision Weight	0.260	0.243	0.164	0.117	0.108	0.109
Nonlinear Weight*	0.137	0.150	0.124	0.114	0.158	0.318
Subjective Weight	0.240	0.206	0.206	0.143	0.079	0.126

*Nonlinear weight is shown for information only. The weight is dependent on the order in which the cue is entered into the model and should not be compared directly with the other weights.

Table 4. Paired t Tests on Average Individual Cue Weights (Df = 35)

Decision Cue	Weights	Relative	Decision	Subjective
Sales Price	Equal	5.91**	6.07**	3.05**
	Relative		5.07**	4.25**
	Decision			1.00
Expected Yield	Equal	5.95**	7.37**	3.55**
	Relative		4.33**	5.00**
	Decision			3.25**
Use of Resources	Equal	0.82	0.33	2.75**
	Relative		1.01	3.13**
	Decision			3.38**
Anticipated Market	Equal	5.86**	4.74**	2.13*
	Relative		5.46**	4.07**
	Decision			2.01
Degree of Government Support	Equal	8.92**	7.58**	8.25**
	Relative		5.57**	1.75
	Decision			2.59*
Availability of Money	Equal	12.50**	7.48**	3.86**
	Relative		11.00**	5.99**
	Decision			1.29

NOTE: Absolute value t statistics are shown.

*Significant difference for alpha level of 0.05.

**Significant difference for alpha level of 0.01.

sub-group of decision makers was computed by regressions done on each sub-sample. These partitioned squared error terms were compared with the aggregate sum of squared error to produce a very sensitive test of equality of regression model of coefficients. Critical F values were based on the number of sub-samples and error degrees of freedom. Table 5 shows the results of the Chow tests across the demographic groups requested by the South Carolina Farm Bureau. All demographic groups exhibited significant differences except the groups partitioned by age, full versus part-time farmers, and those farmers with vocational agricultural training.

Armed with estimated or specified weights, the experimental design was completed. Each set of weights was used to predict each of the 32 decisions based on the setting of the six factor levels. Each prediction was mea[illegible] against the actual decision and the squared error was measured. [illegible] errors were averaged to yield a mean squared error observation per decision maker.

The 32 predicted decisions were then correlated with the actual decisions to yield a simple correlation statistic per decision maker. Therefore, 36 mean square errors and 36 squared bivariate correlations were computed. Tables 6 and 7 present the average mean square error and squared correlation for the 36 decision makers for both the additive linear decision model and the proposed nonlinear, sequential judgment model. Clearly, differences exist which must be discussed.

At this point the analysis of variance proceeded with two models, six weights and their interaction being investigated. The error contributed by variations due to individual decision makers may be removed using a randomized block design with decision makers as blocks.

Table 5. Chow F Tests for Demographic Differences in Decision Models

Demographic Group	Df	Chow F Statistic	Critical F*
Educational Level	35	4.16**	1.70
Farm Acreage	21	3.18**	1.88
Agricultural College Ed.	14	4.83**	2.04
Experience Level	7	2.88**	2.64
Age	7	1.61	2.64
Dollar Sales Volume	7	3.48**	2.64
Full vs. Part-Time Farmer	7	1.28	2.64
Vocational Ag. Training	7	1.64	2.64

*The critical F statistic for alpha = 0.01.

**Reject within the hypothesis that the regression models are the same within the demographic group.

Table 6. Average MSE for the Soybean Production Exercise (N = 36)

Weights	Linear Model	Nonlinear Model
Decision Weights	2.17	2.74
Equal Weights	3.36	2.53
Nonlinear Weights	4.09	2.18
Relative Weights	3.83	4.96
Subjective Weights	3.30	4.18
Subjectively Ranked Weights	3.35	2.85

Table 7. Average Squared Bivariate Correlation for the Soybean Exercise (N = 36)

Weights	Linear Model	Nonlinear Model
Decision Weights	0.766	0.767
Equal Weights	0.540	0.730
Nonlinear Weights	0.469	0.759
Relative Weights	0.741	0.689
Subjective Weights	0.638	0.601
Subjectively Ranked Weights	0.540	0.660

Table 8 presents the analysis of variance table for the soybean exercise when mean square error was used as a response variable. Note the highly significant model as a whole. The R-square is 0.74. The choice of decision model was not significant but the model-weight interaction was highly significant. The analysis of treatment effects was therefore dependent on the interactive model and weight effect.

Table 9 presents the analysis of variance for the soybean exercise when squared bivariate correlation was used as the response variable. The overall model was significant as well as both treatments and their interaction. Note that in both Tables 8 and 9 the use of a randomized block design removed large portions of error variability. This was expected since decision makers exhibit highly variable decision making behavior. Analysis of the contrasts and tests of the research hypotheses follow the results of the second decision making exercise.

Job Selection Decision Making Exercise

The analysis of the job selection exercise proceeded in identical fashion to the soybean production exercise. A total of 21 students completed a job selection exercise (Appendix B) which required them to rate a job described by three factors set at one of three levels. These decisions were recorded and serve as the observations. Since no demographic groups were of interest an analysis via Chow's F test was not necessary. As in the soybean exercise, weights were either estimated or specified by the decision maker. These weights are summarized in Table 10. The paired t tests are presented in Table 11. As in the soybean exercise the weights were highly variable and significantly different

Table 8. ANOVA Results for the Soybean Production Exercise with Mean Square Error as the Response Variable

Source	DF	SS	MS	F
Model	46	1011.84	21.99	23.99*
Error	385	352.89	0.92	
Total	431	1364.57		
Block	35	721.26		22.48*
Model	1	1.28		1.39*
Weight	5	165.05		36.01*
Model x Weight	5	124.09		27.08*
R-square = 0.7414				

*Significant effect at alpha = 0.01.

Table 9. ANOVA Results for the Soybean Production Exercise with Squared Bivariate Correlation as the Response Variable

Source	DF	SS	MS	F
Model	46	7.84	0.170	23.98*
Error	385	2.74	0.007	
Total	431	10.58		
Block	35	3.74		15.04*
Model	1	0.78		109.91*
Weight	5	1.61		45.28*
Model x Weight	5	1.71		48.09*
R-square = 0.7413				

*Significant effect at alpha = 0.01.

Table 10. Comparison of Mean Weights for the Job Selection Exercise

Weight	Salary Level	Geographic Location	Promotion Potential
Weight	0.333	0.333	0.333
Relative Weight	0.475	0.304	0.221
Decision Weight	0.419	0.319	0.262
Nonlinear Weight*	0.634	0.167	0.199
Subjective Weight	0.436	0.283	0.280

*Nonlinear weight is shown for information only. The weight is dependent on the order in which the cue is entered into the model and should not be compared with the other weights.

Table 11. Paired t Tests on Average Individual Cue Weights (Df = 20)

Decision Cue	Weights	Relative	Decision	Subjective
Salary Level	Equal	4.65**	5.50**	3.87**
	Relative		3.58**	1.14**
	Decision			0.64
Promotion Potential	Equal	3.68**	3.12**	1.72
	Relative		4.06**	2.98**
	Decision			0.96
Geographic Location	Equal	0.75	0.51	1.39
	Relative		1.17	0.66
	Decision			1.38

NOTE: Absolute value t statistics are shown.

** Significant difference for alpha level of 0.01.

from one another. Note that with fewer decision cues there were fewer significant differences than in the soybean exercise.

The weights were used to estimate the mean square error and bivariate correlation for each of the 21 decision makers. These observations became the response variables for the analysis of variance procedure. The average mean square error for the job selection exercise is shown in Table 12. The squared bivariate correlations are shown in Table 13. It was interesting that the job selection exercise generated smaller mean square errors and larger correlations on the average than the soybean exercise. This may be explained by the simpler nature of the job selection exercise where only three cues were used. It is also possible that the use of three levels of the decision cues were more representative of the real world instead of the two level, black/white cue description in the soybean exercise.

Again analysis of variance procedures using a randomized block design were completed to determine the treatment effects. Table 14 presents the ANOVA results for the job selection exercise when mean square error was the response variable. Table 15 presents the ANOVA results when the squared bivariate correlation was the response variable. Note the significant interactive effect as well as the overall high significance of the treatments as a whole. The contrasts of interest were identical to the soybean exercise. That is, the research objectives were the same regardless of the individual decision making exercises. It was desired to determine the predictive power of the nonlinear model versus the linear model across the several choices of factor weights and to ascertain whether either judgment model was preferred over the other.

Table 12. Average MSE for the Job Selection Exercise (N = 21)

Weights	Linear Model	Nonlinear Model
Decision Weights	1.59	2.23
Equal Weights	2.31	1.84
Nonlinear Weights	2.88	1.59
Relative Weights	1.85	2.90
Subjective Weights	2.25	3.37
Subjectively Ranked Weights	2.31	2.17

Table 13. Average Squared Bivariate Correlation for the Job Exercise (N = 21)

Weights	Linear Model	Nonlinear Model
Decision Weights	0.864	0.788
Equal Weights	0.788	0.833
Nonlinear Weights	0.728	0.864
Relative Weights	0.835	0.737
Subjective Weights	0.789	0.690
Subjectively Ranked Weights	0.788	0.794

Table 14. ANOVA Results for the Job Selection Exercise with Mean Square Error as the Response Variable

Source	DF	SS	MS	F
Model	31	224.64	7.25	26.13*
Error	220	61.01	0.28	
Total	251	285.65		
Block	20	155.87		28.10*
Model	1	1.49		5.37**
Weight	5	19.85		14.32*
Model x Weight	5	47.42		34.20*
R-square = 0.7864				

*Significant effect at alpha = 0.01.

**Significant effect at alpha = 0.05.

Table 15. ANOVA Results for the Job Selection Exercise with Squared Bivariate Correlation as the Response Variable

Source	DF	SS	MS	F
Model	31	1.19	0.038	14.58*
Error	220	0.58	0.003	
Total	251	1.77		
Block	20	0.53		10.09*
Model	1	0.01		4.49**
Weight	5	0.18		13.52*
Model x Weight	5	0.47		35.63*

R-square = 0.6726

*Significant effect at alpha = 0.01.

**Significant effect at alpha = 0.05.

Summary Analysis of Variance Results

The analysis of variance procedure was based on a completely randomized block design where two response variables were measured. Two ANOVA models were run for each exercise to determine the treatment effects with regard to mean square error and squared bivariate correlations. There were 36 replications per cell in the soybean production exercise and 21 replications in the job selection exercise.

The factors which were varied were the linear versus the nonlinear model and the choice of one of the six weighting schemes. The error contributed by the individual decision makers was blocked from error sum of squares. Finally, it was important to compute the interaction effects of decision model and weight.

The interaction effect was highly significant. This finding, which should be expected, means that the conclusions must be based on analysis of the model-weight choice and not solely on the basis of weights or model alone. The need to keep the experiment-wise error rate down dictated the use of advanced techniques to compare each model and weight with every other combination. Tukey comparisons and Bonferroni contrasts were utilized to analyze the performance of the weights within models and the performance of models across weights. Results are presented on a hypothesis testing basis where each of the five research hypotheses are discussed separately.

Hypothesis H1

Hypothesis H1 is formulated as:

> There is no statistically significant effect on the decision maker's ratings that is explained by the individual cues or interactive terms in either decision making exercise.

This hypothesis was tested by observing that 100% of the regression models in both exercises were statistically significant at the 5% level.

The average R^2 for the soybean exercise was .7921 for the soybean production exercise and .8711 for the job selection exercise. When interactive elements of the decision cues were included the explanatory power of both models increased. However, the R^2 adjusted for degrees of freedom was larger for the main effects model.

It is concluded that knowledge of information factors (cues) does have a statistically significant effect in explaining decision maker behavior and that interactive ... are not significant.

Hypothesis H2

Hypothesis H2 is formulated as:

> There is no statistically significant difference between the decision maker's subjective cue weights and the relative weights derived from the compensatory model in either decision making exercise.

This hypothesis was tested by observing the distribution of subjective weights and relative weights to determine if significant differences exist. Paired t tests were used to compute the probability that the difference between them is zero. Tables 3 and 10 present the average weights for the decision making exercises. Tables 4 and 11 present the paired t statistics.

The overwhelming evidence indicates that there are differences in the importance the decision maker places on a cue and the actual importance. This difference exists whether relative weights or decision weights are considered to be the actual importance of the cue. This conclusion is in agreement with the findings of previous research. Hypothesis 2 is therefore rejected.

Note that subjective weights were in general significantly different than any other set of weights. The fact that the subjective weights in the job selection exercise were not as significantly different from the other weights may be attributed to the fact that a less complex model with fewer cues was being utilized. Therefore, there may have been less propensity to mis-estimate the subjective weights. In fact, equal weights were different from subjective weights in only one cue, the salary level!

Overall, it is concluded that the decision makers displayed a lack of insight with regard to cue weight. The less significant findings for the job selection exercise is attributed to a less complex and therefore inherently less variable decision model. It is noted that the decision makers generally place more weight on factors of importance than they will admit and tend to overestimate the weight of factors which are of little actual weight.

Hypothesis H3

Hypothesis H3 is formulated as:

> There is no statistically significant difference in the linear regression models derived from the compensatory model among demographic/functional groups in either decision making exercise.

The intent of this hypothesis was to determine if significantly different decision cue weights exist among the various categories of participants in the decision making exercise. In the case of the job selection exercise no demographic or functional groups were identified.

Chow's F tests were computed for the eight categories of soybean farmers. Table 5 presents the results of these calculations. The Chow F test was chosen in lieu of paired t tests so that the overall model could be analyzed versus a weight by weight comparison. Paired t tests could be used to further differentiate the farmers but this additional information is not germane to this research.

Note that all demographic categories exhibited statistically different decision models except groups differentiated by age, full versus part-time farmers and whether or not vocational agricultural training was received. Apparently decisions were made in similar fashion within these demographic groups.

While it is easy to envision why differences exist between decision makers, it is much more difficult to explain why there are not differences. One might argue that educational level, farm size, experience, and sales volume are all measuring the same effect. The primary conclusion is that differences between decision making groups do exist. Certainly the optimal group to study would be those participants who are known to be successful decision makers!

It is concluded that Hypothesis H3 should be rejected. There are differences in decision making behavior across demographic groups of decision makers.

Hypothesis H4

Hypothesis H4 is given as:

> There is no statistically significant difference in the explanatory power of the proposed model and the linear compensatory model in either decision making exercise for subjective, equal, nonlinear, relative or decision weights where each set of weights sum to one.

This hypothesis was intended to determine whether or not a difference between decision models existed across each set of weights. The explanatory power was measured with two response variables, mean square error of prediction and squared bivariate correlation of the prediction with the actual decision.

Tables 6 and 7 present the average mean square error and squared bivariate correlation for the 36 participants in the soybean production exercise. Tables 12 and 13 present these statistics for the job selection exercise. Clearly, differences exist for both response variables.

Hypotheses H4 and H5 were tested using the results of an analysis of variance approach for each response variable. Tables 8 and 9 present the resulting ANOVA table for the respective response variables for the soybean production exercise. Note the highly significant model-weight interaction. Similarly, Tables 14 and 15 present the ANOVA tables for the job selection exercise. Again the interactions are highly significant. Also note the highly significant F statistics. Clearly, treatment effects were present. The significant interaction means that conclusions cannot be made on the basis of decision model alone. Rather the combined effect of model and weight must be discussed.

One way to compare the average performance of the models was to compute the average performance measures of the linear versus the nonlinear model as a contrast. Since only one contrast was of interest to test Hypothesis H4, a Bonferroni comparison was done for each response variable. Table 16 shows the result of this analysis.

Based on the average performance, the only significant difference was found when looking at squared bivariate correlations for the soybean production exercise. In this case the nonlinear model performed significantly better. However this average mixes up the effect of model-weight combinations. Furthermore, both estimated and non-estimated weights were averaged together. The result is an average performance

Table 16. Summary of Bonferroni Comparisons of Average Decision Model Performance

Contrast*	Exercise	
	Soybean	Jobs
Average Bivariate Correlation	Nonlinear	---
Average Mean Square Error	---	---

*This table indicates the model whose average performance across all weights was significantly different and preferred at alpha = 0.05.

across all six cue weights. It is difficult to guarantee what this average really measures.

It is concluded that categorical statements about the average performance of the proposed model are of limited value. The evidence slightly favors the nonlinear decision model. However, it is important to recognize that both models' performance is directly related to the choice of cue weights. Therefore, any statement about preference for a model must be made in relation to the set of weights chosen to implement the judgment model.

Certainly the data do not suggest that the linear model was preferred. At the same time only limited evidence was found to suggest that the nonlinear model was a preferred model.

It is concluded that the nonlinear model performed well in predicting decisions to the extent that it did as well as the well established linear compensatory rule. Therefore, it is concluded that the sequential judgment model is a viable decision modeling alternative and that the concept of sequential use of weighted decision cues is a reasonable and useful way to view the decision making process. The evidence suggests that on the average, given the performance of all the weights, Hypothesis 4 should not be rejected.

It should be noted that the presence of a significant model-weight interaction renders the test of Hypothesis H4 of little value. The significant interaction means that average model performance does not yield the research insight necessary to reach overall conclusions. Hypothesie H5 tests the specific differences in decision model performance within decision models and across all six weights.

Hypothesis H5

Hypothesis H5 is given as:

> There is no statistically significant difference in the explanatory power of the subjective, relative, equal, nonlinear, or decision weights in either the linear or proposed compensatory model.

Although the overall comparisons only marginally favored the nonlinear model, it is critical to recognize the interactive nature of the results and interpret the performance of each model in the context of which set of weights was used. Therefore, contrasts were computed across decision models for each set of weights. These contrasts were computed for both response variables. Tables 17 and 18 show the performance measures for each model and weight for both decision exercises.

First note that the nonlinear model is preferred when the estimated nonlinear weights are used. This is intuitively appealing.

Note that when subjective weights were used the linear model was generally preferred for both decision making exercises. However, recall that subjective weights were usually in error due to the lack of insight phenomenon and result in poor predictions. The finding here indicates that subjective weights result in less poor performance if used in the linear model.

The use of decision weights only marginally favored the linear model. This is interesting since decision weights were estimated for the linear model. Apparently the nonlinear, sequential model made good use of weights that accurately reflect the importance of a cue, even when the weights were estimated for a different model!

Table 17. Summary of Tukey Comparisons Across Decision Models (Mean Square Error)

Contrast	Mean Square Error*	
	Soybean	Jobs
Linear vs Nonlinear @ Equal Wts	Nonlinear	---
Linear vs Nonlinear @ Decision Wts	---	Linear
Linear vs Nonlinear @ Nonlinear Wts	Nonlinear	Nonlinear
Linear vs Nonlinear @ Relative Wts	Linear	Linear
Linear vs Nonlinear @ Subjective Wts	Linear	Linear
Linear vs Nonlinear @ Subjectively Ranked Wts	---	---

*The table indicates which model yielded significantly better mean square error of prediction between predicted and actual decisions at alpha = 0.05 for each exercise.

Table 18. Summary of Tukey Comparisons Across Decision Models (Squared Bivariate Correlation)

Contrast	Bivariate Correlations*	
	Soybean	Jobs
Linear vs Nonlinear @ Equal Wts	Nonlinear	Linear
Linear vs Nonlinear @ Decision Wts	---	---
Linear vs Nonlinear @ Nonlinear Wts	Nonlinear	Nonlinear
Linear vs Nonlinear @ Relative Wts	---	Linear
Linear vs Nonlinear @ Subjective Wts	---	Linear
Linear vs Nonlinear @ Subjectively Ranked Wts	Nonlinear	---

*The table indicates which model yielded significantly better bivariate correlation between predicted and actual decisions at alpha = 0.05 for each exercise.

Finally, the nonlinear model tended to make better use of equal weights. This was true when the cues were properly rank ordered (equal weights) or subjectively ranked.

While these contrasts were useful in describing the overall performance of the alternative models, range tests were completed to determine the relative value of the weights within each decision model. It is evident from the significant interaction that paired comparisons must be done for each cell in the experimental design. This requires 15 comparisons per decision model per response variable. Use of ordinary paired t tests would result in a very high probability of error. Therefore each contrast was compared using Tukey multiple comparisons where the experiment-wise error was set to 5%.

The individual contrasts are not shown here. Rather the graphical technique widely used in ANOVA studies is employed where the response variables are rank ordered and then joined by a line if there is not a statistically significant difference between them. Figures 6 and 7 contain the multiple comparisons for each response variable for both decision making exercises.

Figure 6 contains the results for the linear compensatory model. It is no surprise that the statistically estimated weights out-perform the simple weights in every case. A vital conclusion is that decision weights, while not always significantly better, are preferred to relative weights. This conclusion confirms the previously discussed nature of relative weights being the contribution of a cue to the explanatory power of an individual decision model not the actual importance of the cue itself.

Figure 6. Tukey Comparisons of Average MSE and Squared Bivariate Correlation Between Weights for the Linear Decision Model with an Experimentwise Confidence Level of 95%

Soybean Production Exercise

	DW	SW	SR/EW	RW	NW
MSE:	2.2	3.3	3.36	3.82	4.09

	NW	SR/EW	SW	RW	DW
r^2:	.47	.54	.64	.74	.77

Job Selection Exercise

	DW	RW	SW	SR/EW	NW
MSE:	1.6	1.8	2.3	2.31	2.87

	NW	EW/SR	SW	RW	DW
r^2:	.73	.78	.79	.83	.86

NOTE: EW = Equal Weights
DW = Decision Weights
NW = Nonlinear Weights
RW = Relative Weights
SR = Subjectively Ranked Weights
SW = Subjective Weights

Figure 7. Tukey Comparisons of Average MSE and Squared Bivariate Correlation Between Weights for the Nonlinear Decision Model with an Experimentwise Confidence Level of 95%

Soybean Production Exercise

	NW	EW	DW	SR	SW	RW
MSE:	2.2	2.5	2.7	2.9	4.2	5.0

	SW	SR	RW	EW	NW	DW
r^2:	.60	.66	.68	.73	.76	.77

Job Selection Exercise

	NW	EW	SR	DW	RW	SW
MSE:	1.6	1.8	2.16	2.23	2.9	3.37

	SW	RW	DW	SR	EW	NW
r^2:	.69	.74	.78	.79	.83	.86

NOTE: EW = Equal Weights
DW = Decision Weights
NW = Nonlinear Weights
RW = Relative Weights
SR = Subjectively Ranked Weights
SW = Subjective Weights

Clearly, the nonlinear weights performed much worse in the linear model than other weights, even subjective or equal weights. Also, it is noted that in the linear model equal weights did not out-perform the other weights although in some cases they cannot be found different from the subjective weight performance.

Figure 7 shows the resulting pair-wise comparisons for the non-linear, sequential decision model. An entirely different result emerges. First, note the overall outstanding performance of the non-linear weights. This was expected since it was known that nonlinear weights were estimated for the sequential model. Second, the use of relative weights is overwhelmingly rejected. Relative weights, since they do not imply knowledge of the actual importance of the cue finish at or next to last.

Decision weights on the other hand did imply the importance of the cue and perform quite well, particularly in the soybean production exercise. In fact they were sometimes indistinguishable from the performance of known optimal weights! The implication is that if the importance of a cue is known or can be estimated, even with a different model, the sequential judgment process can make good use of those weights.

The somewhat startling conclusion is the performance of the equally weighted factors in the sequential model. The equally weighted and properly rank ordered cues are not significantly different from the statistically estimated model! In addition, the subjectively ranked equal weight cues performed better than linear model weights and only once were statistically different than equal weights in optimal order.

This unexpected performance of the equally weighted model is significant in that it suggests a logical conclusion. Decision makers have been shown to lack insight when it comes to estimating weights for cues. However, the decision maker may be able to rank order them quite well. Very good models result if the cues are rank ordered and used in the sequential judgment model with equal weight. Since equally weighted cues require no estimation effort, substantial reduction in implementation overhead to install a decision support system may result if the sequential judgment model is used.

It is concluded that significant differences do exist in explanatory power between weights which is also dependent on the decision model choice. The choice of weights is a function of the decision model. Likewise, if a set of weights is to be used, then the model which best uses those weights should be chosen. Hypothesis H5 is, therefore, rejected.

CHAPTER V

SUMMARY AND CONCLUSIONS

This chapter summarizes the research objectives, methodology and results. General conclusions are presented as well as a discussion of the implications of this research in other related disciplines. Suggestions for further research complete this chapter.

Overview

This research effort is designed to investigate the nature of a proposed model of human judgment. Previous research has established the need and applicability of statistical modeling in describing the behavior of decision makers. This research presents the basic theory supporting decision models as well as weaknesses of current linear models.

A decision model based on sequential combinations of decision factors and their weights is developed. This model is motivated by previous research findings that interactive elements of statistical models are rarely significant. This finding suggests that the human brain may in fact be a sequential processor unable to simultaneously process sets of cues and weights.

Simulations of decision maker behavior were used to provide observations which can be modeled with alternative decision models and sets of weights. Statistical models such as ANOVA were used to determine the overall performance of the proposed model as well as the linear compensatory decision model. Conclusions are developed based on the analysis of contrasts indicated by the ANOVA results.

The proposed model was found to be an acceptable model of decision making. Discussion of the implications of sequential decision processes is presented. Examples of the application of the sequential judgment model are included in the appendices. Suggestions for further research complete this research effort.

Summary of the Research Objectives

The primary objective of this research is to compare the explanatory power of a proposed, sequential decision model with the traditional, linear compensatory model. This objective is directly related to testing hypotheses concerning the processing nature of the brain in making judgments. Toward that end additional sub-objectives are specified.

First, the basic theory of judgment was presented. Human judgment is viewed as some combination of decision factors and their importance. The crucial question is which factors should be used, how should they be weighted, and in what manner are the factors and their weights combined? The linear compensatory model has evolved as an extremely flexible and robust statistical model.

A primary concern is whether or not the robust, linear model in fact models the decision making process or simply describes the statistical nature of the process results. That is, the fact that linear models are useful does not establish that the original process was in fact a linear combination of factors and weights. Certainly the evidence in the physical world overwhelmingly supports the concept of complex interactions among factors in a process. The whole philosophy of calculus is based on the interrelation of explanatory variables.

Previous research has established that a human decision maker rarely makes use of any interaction among decision factors. This finding suggests the possibility that the brain is a sequential device much like current computer architectures and is inherently unable to process simultaneous information.

Secondary objectives of this research include the development of an alternative decision model which is sequentially oriented. This model is nonlinear in nature and requires nonlinear estimation techniques to establish the weights to be compared with the linear compensatory model. Therefore, an additional objective is to develop an estimation technique suitable for estimating factor weights for the proposed model.

In order to investigate the nature of the proposed model and to compare it with the linear compensatory model, some means of comparison must be established. The use of policy capturing experiments provide an extremely powerful and convenient source of human judgments where the decision factors are controlled by the researcher. This technique is, in effect, simulation of human judgment. The analysis of the results of the simulation follow conventional wisdom by performing analysis of variance experiments and computing appropriate contrasts.

Finally, an objective of this research is to present the implications of a successful sequential decision model in other disciplines. Considerable research is currently devoted in management theory, economics, decision theory, computer science, physiology and artificial intelligence toward understanding human judgment. These disciplines all make use of models of decision making. The fact that sequential judgment is a tractable and viable alternative suggests fresh insight into complex problems.

Summary of the Research Methodology

This research used simulations of human judgment to provide a database of responses to controlled experiments. The responses for each individual decision were used to estimate the optimal weights for both the proposed and traditional linear model. The decision maker was also asked to supply his subjective weights which reflect the importance of a decision factor as the decision maker saw it.

Computation of linear model weights was accomplished in two ways. First, the relative weights were estimated using a technique developed by behavioral decision theorists and widely used in policy capturing research. Second, a restricted model was estimated where the weights were estimated directly. The computation of relative weights is dependent on the orthogonal nature of the policy capturing experiment and is limited to controlled experimentation. The restricted model estimation technique generates decision weights which are not dependent on any experiment design and can be computed based on real world non-experimental data.

Equal weights were also included to test the performance of both decision models when the weights were unknown. The use of equal weights has been suggested by previous research as a simple mechanism which may yield acceptable results.

Two independent policy capturing experiments were completed. One experiment included six factors set at one of two levels while the second consisted of three factors set at one of three levels. Use of two independent and unrelated experiments add validity to the results and allow comparisons across different policy capturing experimental designs.

Two response variables were measured as an indicator of model performance. The use of linear model explanatory power, F statistics, and other standard statistical descriptions were not possible since both nonlinear and restricted linear models are estimated and compared with the conventional least squares estimation technique of linear models. Furthermore, the use of equally weighted factors as well as subjective weights do not yield these statistics.

The two response variables were the mean squared error of prediction and the squared bivariate correlation between the prediction and the actual decision maker responses. The mean squared error was computed by predicting the decisions of each decision maker. These predictions were subtracted from the actual decisions and squared. The average mean squared error was recorded for each decision maker and served as one replication of each model and weight combination in the analysis of variance experiment. The mean square error is a well defined response variable suitable for statistical analysis and is the best overall performance measure.

The squared bivariate correlations were computed by measuring the Pearson correlation between the predicted decisions and the actual decisions of each decision maker. The correlation was squared to yield a simple coefficient of determination. This response variable does not imply any statistical relationship between the predictions and actual responses. Rather, it is a measure of the degree to which the responses vary with the predictions. As such, it is a measure of the consistency of each decision model and weight in predicting decision maker responses, albeit at an unspecified error.

The research methodology was aimed at five research hypotheses. These hypotheses test the applicability of decision models in explaining human decision making, the degree to which a decision maker knows the importance of factors in the decision, whether or not differences in decision making behavior can be attributed to demographic differences, whether or not the linear or sequential decision model is preferred, and to what extent the choice of weights affects the performance of either decision model. These hypotheses were tested based on the results of two independent policy capturing exercises where the same statistical tests were performed on each exercise.

The overall usefulness of decision models was determined by the average R-squares of the linear decision model. The ability of a decision maker to estimate accurately the weight of a decision cue was tested by paired t tests between the subjective weights and the estimated weights for each decision maker. The differences in decision making behavior across demographic groups of decision makers was tested by estimating conventional linear models for each sub-group of the original set of decision makers using F tests to determine if those regression models differ significantly from the aggregate, group regression model.

The hypotheses concerning the primary objective of this research, that is, the performance of the proposed model versus the linear compensatory model, were tested based on the analysis of variance for the two previously mentioned response variables. Each policy capturing experiment was analyzed separately for each response variable. Appropriate contrasts were computed which test the overall performance of the models across each set of weights and the performance of each set of weights within each decision model. Since these tests require multiple comparisons, the experimentwise confidence level was established in advance and contrasts were evaluated using Tukey and Bonferoni techniques.

Summary of the Results

The findings of this research fall into two categories. First, results which pertain to individual decision making and second, results which apply to comparing the alternative decision models. The first set of results were completed to confirm the findings of previous research. The second set of results address the primary objective of this research.

The application of linear decision models was found to be statistically significant in describing decision maker behavior. Decision makers behaved in a consistent fashion attested to by much previous research. The use of interactions between decision cues was deemed insignificant. That is, the decisions could be accurately predicted with knowledge of the main cue effects only. Again, this finding is in agreement with previous research.

It was found that decision makers do not estimate the actual importance placed on decision factors well. In most cases, the subjective weights were different from estimated weights even at an alpha level of 1%. It was noted that the decision weights, those weights estimated by restricting a linear model, were not as significantly different as the relative weights. This finding tends to suggest that relative weights do not actually measure the importance of a cue and that previous research indicating a lack of insight on the part of decision makers, while still true, may not be as severe as previously indicated.

Differences in decision making behavior did exist between demographic groups of decision makers. Again, this agrees with previous research and is intuitively appealing. Nevertheless, not all demographic groups displayed differences. It is difficult to explain why these groups did not employ significantly different decision making strategies. Nor is it easy to explain why other groups did use different models. The point is that the possibility of significantly different views of a problem can result among groups of decision makers and this situation must be recognized.

The analysis of each decision model's performance revealed several results. In terms of the ANOVA results, it was found that the application of a decision model with suitable weights explained a significantly large proportion of total variability. That is, the performance indices chosen were largely explained by the treatment effects of decision model and factor weight. Furthermore, the interaction of decision model and factor weight was highly significant. This finding indicates that categorical statements about the performance of either decision model are meaningless, since the combined effect of a decision model and specific set of weights vary across the alternative models and weights.

By contrasting the average performance of the proposed sequential model versus the linear compensatory model, it was found that the proposed model was marginally preferred. This was primarily due to the ability of the sequential model to make better use of non-optimal weights. This finding is of limited value since an average performance across all sets of weights obscures the known interactive effect of model-weight interaction.

Each decision model's performance was evaluated for each alternative set of weights by computing paired contrasts. It was found that the sequential model was always preferred when the weights used were the estimated sequential model weights. When subjective weights were used, the linear model was preferred. Likewise, when relative weights were employed, the linear model performed best. When decision weights were used, the linear model was marginally preferred. Finally, when equal weights were used, regardless of the order used, the sequential model was preferred.

While the findings across models by weight is informative it does not tell the whole story. Therefore, contrasts between each model-weight pair for both response variables in each decision making experiment were completed. Since this analysis required many comparisons, Tukey tests were used to hold the overall experimentwise error to 5%.

The results of this analysis revealed very interesting findings. When a linear compensatory model was employed, the decision weights performed significantly better than other weights except when the performance index was correlation of predictions with actual responses. In that case, relative weights performed as well. Weights estimated for the sequential model performed worst in the linear model, as expected. The use of equal weights or subjective weights did not perform well, although in general they could not be distinguished from one another.

A very different result was obtained when the proposed sequential model was used. The sequential model performed best when the weights estimated for it were used. This is certainly no surprise. However, the sequential model performed well using the decision weights estimated for the linear model. Surprisingly, the sequential model performed as well with equally weighted cues as it did with the optimal weights estimated for it! This finding is noteworthy, since it indicates a decision model with very good performance is possible without the expense of estimated weights. Finally, the sequential model performed poorly when subjective or relative weights were used. This is further confirmation of the lack of insight phenomenon and the limited value of relative weights.

In summary, the results confirmed the findings of previous policy capturing research and established that the theory of a sequential decision model is valid and tractable. Furthermore, the evidence indicates that the sequential model, while not categorically preferred over the linear compensatory model, does exhibit better performance when equally weighted cues are used and that weights can be estimated for it which make its performance at least as good. The contribution of this research is not an improvement in the explanatory power of decision models but an alternative decision model which makes better use of cue weights, particularly those weights obtained without estimation techniques.

This contribution makes the application of decision models dramatically simpler since no experimentation or estimation of weights is required to implement the model. The primary objective of modeling the decision making process as a sequential combination of cues and weights is deemed successful. The ability of the sequential model to explain human judgment suggests numerous potential applications discussed later.

Conclusions

Several general conclusions can be offered as a result of this research. A proposed decision model and supporting theory have been discussed. This model is based on the concept of sequentially processing decision factors and their importance reflected by factor weights. An extremely visual presentation of the proposed model is possible which depicts the progression of the alternative's rating as factors are brought into the model. The model has been formulated so as to allow estimation of the decision factor weights, albeit with a sophisticated nonlinear estimation technique.

It is concluded that the sequential model is a useful and statistically valid decision model. It is able to predict decisions as well as the linear compensatory model given that the proper set of weights is employed. It is concluded that the primary research contribution is an alternative way to view the human judgment process which is theoretically appealing and experimentally supported. This finding provides a basis for discussion of the impact of the proposed sequential processing concept in other related disciplines.

The unexpected conclusion is that the use of equally weighted decision factors can be used in conjunction with the sequential decision model to yield extremely good decision model performance. This finding is significant in that it redefines the concept of equal weight. That is, it is not as important to know the relative importance placed on a decision cue as to know the relative order in which the cue is processed.

This concept is fundamentally different from previous research and decision models. The fact that sequential judgment models work suggests that the brain may in fact be a sequential device which is unable to process interactive cue combinations. The performance of equally weighted factors indicates that in a sequentially based decision model the marginal contribution of a factor is not its importance relative to other factors but the order in which it is processed.

The overall performance of the sequential model provides a fresh approach to decision modeling. The implications for decision support systems, management theorists and artificial intelligence researchers are potentially valuable.

Numerous applications of decision modeling occur in management settings from production scheduling or quality control to strategic planning. The idea that decisions could be modeled as a sequence of decision cues with some weight (possibly equal) opens up alternative ways to provide support to managerial decision making. The widespread and growing proliferation of computer based decision models could easily adopt the proposed sequential technique. The relevant question for the user becomes how do I rank order pertinent factors rather than what are the factors' relative weights? Given evidence that subjectively assigned weights are usually in error, the sequential technique may prove substantially better than ad hoc assignment of relative cue weight.

An interesting view of the sequential decision theory is obtained if economic principles are considered. Recall that classical economic theory makes use of so-called utility functions which describe the marginal contribution of a good toward a consumer's subconscious satisfaction. The marginal contribution of a single good or factor of a production function has associated with it a marginal rate of technical substitution (MRTS) which reflects the relative importance of that good or factor. Clearly the MRTS is similar to what has been described as a decision cue weight. The successful implementation of sequential decision models suggests that the same phenomenon may be applicable to economic consumption and production functions!

Another area of current research involved in decision theory is the area of artificial intelligence and expert systems. These disciplines are attempting to directly mirror the decision making process with complex algorithms based on extensive gathering of expert behavior. Most algorithms are based on some linear combination of decision cues and a set of sequential logic checks to attempt to achieve a previously specified optimal answer. The ultimate goal is to create an algorithm which can learn from experience and dynamically restructure the algorithm's progress when using fuzzy rules and decision criterion.

Since a computer is a sequential device, it is interesting to speculate on the impact of designing artificial intelligence algorithms based on the assumption of a sequentially driven human decision making process. It is expected that fundamentally different designs would result.

Certainly, this research finding is relevant to research in learning, brain physiology and neurological processes. Although little is known of the nature of memory, learning and recall, it is possible that the theory which supports sequential decision making is synergistic with the electro-chemical transmissions within the brain.

Finally, an additional implication of this research is the potential for an alternative statistical model. Consider that any linear regression model could be formulated as a sequential model. Although not a part of this research, a sequential model incorporating two-way interactions can be constructed. The result is a volumetric hyperspace versus an area representation presented in this research.

In summary, an alternative way of viewing the decision making process has been developed. The sequential model has been found to be an acceptable model of human judgment. The proposed model makes exceptionally good use of equally weighted, properly rank ordered decision cues. This finding suggests reevaluating the meaning of the marginal contribution of a decision cue since the sequential model uses both factor weight and order to describe decision maker behavior.

Suggestions for Further Research

Several suggestions for additional research are offered. Certainly, additional experiments to validate this research are recommended. However, other more noteworthy efforts are worth consideration.

First, there exist many applications in management, engineering and behavioral psychology which could be used to implement decision support systems using both linear and sequential models. Current interest in computerized decision support provides fertile ground for this effort.

Second, replications of this research should be completed where the sterile environment of policy capturing experiments is relaxed. That is, decision models should be developed in the context of live, real-world data. A classic example would be production planning or strategic management. The use of decision weights is well defined in this environment and has been shown to be attractive candidate weights for this type decision model.

Third, current artificial intelligence theory should be meshed with decision model research to attempt the construction of decision models that can learn. Ambitious as it may seem, this area may well be the next epoch in technological achievement.

Finally, the general nature of statistical modeling could be investigated to ascertain the impact of sequential modeling on standard regression applications. The very nature of computer architecture as a sequential device lends itself to thinking of statistical modeling as an extension of sequential logic.

In conclusion, this research effort has achieved its primary objective. An alternative decision model has been developed, described and tested. The results of this research suggest the basic theory of a sequential model of human judgment and support several additional research areas.

APPENDICES

INSTRUCTIONS

1. First, fill in the Personal Identification Code sheet on page 1. We will send your personal analysis to you if you provide us with an address.

2. Second, fill in the Background Information sheet on page 2. This data allows us to compare other farmers with your analysis. You will be sent the results of this work.

3. Each soybean crop is desribed by six criteria. These criteria are described on page 3. Take time to read over each one.

4. Now fill in the Estimated Importance sheet on page 4. This data will allow you to compare the computer's analysis against what you think is most important to you.

5. You will be presented with 36 different soybean crops. Each crop is rated on 6 criteria that are described on the Crop Description Criteria page of this exercise. Simply circle the rating you would give this crop based on the information provided. Do not try to reason out a response. Rate the crop based on your experience and judgment. **An example rating is shown on page 5.**

6. The exercise takes about 30 minutes to complete. When you are finished, return the exercise to Clemson University in the envelope included in this packet. You will receive your personal analysis and the group averages in several weeks.

Thank you very much for your participation!

Personal Identification Code

In order to identifiy your responses a personal identification number will be used. Your responses are stored in the computer by this number so that no one can determine your individual decisions. The computer will perform the analysis and print out the results by the identification number. If you wish to receive your analysis we must have your name and address. The results will be tabulated by computer and mailed directly to you. Your name and address will be stored separately from the exercise responses and will not be used for any purpose other than to provide the mailing instructions.

1. Write the month and day of your birthday as a 4 digit number .... ________
   Example: March 12 would be 0312
2. Write the last 4 digits of your phone number ________
3. Add these two numbers .... ________
4. Write the last 4 digits of the number in line 3 .... ________

The last number is your personal identification number. Please write it where you can find it later so that you may find your exercise results.

Name: ____

Street: ____

Town: ______________________ State _____ Zip _______

Background Information

In order to compare farmers with different backgrounds and types of farm operations we would appreciate response to the items below. Omit any item you do not wish to answer.

Please check the box which most closely describes your farm operation.

Number of acres in Soybeans: ☐ 100 or less ☐ 101 - 250 acres ☐ 250 - 500 acres ☐ Over 500 acres

Sales of all Farm products:
☐ More than $100,000 in yearly sales
☐ Less than $100,000 in yearly sales

Full or Part-time Farmer:
☐ More than 50% of net income from farm
☐ Less than 50% of net income from farm

Farm experience: ☐ More than 15 years ☐ Less than 15 years

Age: ☐ More than 35 years old ☐ Less than 35 years old

Education:
☐ None of the following
☐ High school graduate
☐ TEC School graduate
☐ 2 year college graduate
☐ 4 year college graduate
☐ Advanced or Professional graduate

Did you receive vocational agricultural training in high school?

☐ Yes ☐ No

If you attended school after high school, was your education

☐ Agricultural ☐ Non-agricultural

Soybean Crop Description

Six criteria will be used to describe each alternative soybean crop. Each criteria is briefly explained below. The order in which the criteria is presented is random and does not imply the importance of each of the criteria.

Use of Land, Labor and Equipment - An indicator of how well the resources of the farm are utilized. A marginal rating means that sufficient resources are questionable. An excellent rating means that sufficient resources are available and land and equipment are used efficiently.

Degree of Government Support - An estimate of the value of any government support or price guarantee. A marginal rating means an unfavourable program. An excellent rating means a program which reduces risk to an acceptable level.

Estimated Commodity Sales Price per unit - An estimate of the sales price per bushel. A marginal rating means an acceptable but just a breakeven price. An excellent rating means an acceptable and better than average price.

Anticipated Market Demand for Soybeans - An estimate of the soybean demand at the time of sale. A stable demand means an acceptable but weak market. An expanding demand means an acceptable and growing market.

Probability of Producing Your Average Yield - An estimate of the productive capacity of your farm. A marginal rating indicates some doubt as to whether the soil, weather factors and environment will produce an average yield. An excellent rating means that average production is expected and probable.

Availability of Money - An estimate of the availability of money needed to plant, care for and harvest the soybean crop. A marginal rating means that average debt is expected but interest rates are high and money is more difficult to obtain than usual. An excellent rating means that average debt is expected and money is available at acceptable interest rates.

Estimated Importance

Given the six criteria on the previous page, estimate how much weight you put on each of these criteria. Distribute 100 points amoung the six criteria so that the most important criteria is given the most points. Make sure that the total of all the points is 100.

Criteria

Criteria	Points
Use of Land, Labor, and Equipment	________
Degree of Government Support	________
Estimated Commodity Sales Price per unit	________
Anticipated Market Demand for Soybeans	________
Probability of Producing Your Average Yield ...	________
Availability of Money	________
Total	100

Check to see that you have calculated your Personal Identification Code, recorded your background information, and estimated your weights for the criteria above.

You are ready to begin the exercise. Please evaluate all 36 alternative soybean crops that follow and record your rating directly on the page by circling the appropriate number on the scale following the crop criteria.

An example rating is shown on the next page.

EXAMPLE

Decision: Given the information on the soybean crop below would you increase or decrease production of soybeans on your farm.

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Excellent
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Definitely Decrease Production					Neutral					Definitely Increase Production

Crop Alternative # 1

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Marginal
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Excellent
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 2

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Excellent
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 3

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Marginal
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 4

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Marginal
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Marginal
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production — Neutral — Definitely Increase Production

Crop Alternative # 5

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Marginal
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Excellent
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production — Neutral — Definitely Increase Production

Crop Alternative # 6

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Marginal
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Marginal
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production — Neutral — Definitely Increase Production

Crop Alternative # 7

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Marginal
Estimated Commodity Sales Price per unit	Marginal
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Excellent
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 8

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Marginal
Estimated Commodity Sales Price per unit	Marginal
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Marginal
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 9

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Excellent
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 10

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Marginal
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Excellent
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 11

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Marginal
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Excellent
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 12

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Marginal
Estimated Commodity Sales Price per unit	Marginal
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Marginal
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 13

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Marginal
Estimated Commodity Sales Price per unit	Marginal
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Excellent
Availability of Money	Marginal

Circle on the scale below your ratin; for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 14

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Marginal
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Marginal
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 15

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Excellent
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 16

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Marginal
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Marginal
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 17

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Marginal
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 18

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Marginal
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Marginal
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 19

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Marginal
Estimated Commodity Sales Price per unit	Marginal
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Marginal
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 20

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Marginal
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Marginal
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 21

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Marginal
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 22

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Marginal
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Marginal
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 23

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Marginal
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 24

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Excellent
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 25

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Marginal
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Excellent
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production — Neutral — Definitely Increase Production

Crop Alternative # 26

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Marginal
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Excellent
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production — Neutral — Definitely Increase Production

Crop Alternative # 27

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Marginal
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Excellent
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production — Neutral — Definitely Increase Production

Crop Alternative # 28

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Marginal
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Marginal
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 29

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Marginal
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Excellent
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 30

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Marginal
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Excellent
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 31

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Excellent
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 32

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Marginal
Estimated Commodity Sales Price per unit	Marginal
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Excellent
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 33

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Marginal
Estimated Commodity Sales Price per unit	Marginal
Anticipated Market Demand for Soybeans	Expanding
Probability of Producing Your Average Yield	Excellent
Availability of Money	Marginal

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 34

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Excellent
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Marginal
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 35

Use of Land, Labor and Equipment	Marginal
Degree of Government Support	Marginal
Estimated Commodity Sales Price per unit	Marginal
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Marginal
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

Crop Alternative # 36

Use of Land, Labor and Equipment	Excellent
Degree of Government Support	Marginal
Estimated Commodity Sales Price per unit	Excellent
Anticipated Market Demand for Soybeans	Stable
Probability of Producing Your Average Yield	Marginal
Availability of Money	Excellent

Circle on the scale below your rating for this crop.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Definitely Decrease Production	Neutral	Definitely Increase Production

THANK YOU!

This completes the decision making exercise. Please return the exercise portion of this packet to us for processing. An addressed and stamped envelope is provided for your convenience.

Once again we appreciate your participation in this research. You will receive preliminary results in a few weeks. A sample of participants will be asked to rate a small number of crops to insure the validity of the analysis.

Appendix B

Job Preference Decision Making Exercise

A JOB PREFERENCE
DECISION-MAKING EXERCISE

This decision making exercise deals with hypothetical situations. In this way, it simulates the job preference decisions most professional-level individuals encounter at some point in a career. As you complete the exercise, you should project yourself into a hypothetical situation. Assume you are seeking a job and you are in the process of judging a number of jobs available to you which you are qualified to fill. These jobs differ only in regards to the information presented to you about three key factors. A sample job is presented below for your advance examination before you begin the exercise.

Sample Job

In this job, the likelihood that you will...

...live in a desirable geographic location is.....................MEDIUM (50%)

...be promoted within two years is............................VERY HIGH (90%)

...receive a salary at an above average level is..................MEDIUM (50%)

Decision A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

As you arrive at your decisions, the characteristics of the information presented to you about each job should be kept in mind. If an event's likelihood is Very High (90%), then it will occur in about 90 of 100 similar situations. If an event's likelihood is Medium (50%), then it will occur in about 50 of 100 similar situations. If an event's likelihood is Very Low (10%), then it will occur in only about 10 of 100 similar situations.

In each instance, consider the information presented to you and then arrive at your judgment of the attractiveness of that particular job to you. Circle the number under DECISION A which indicates your choice. Remember, there are no "correct" or "incorrect" choices, so follow your own feelings.

You should now begin to make the actual decisions, starting with Job #1. Be careful not to skip a job; you should make decisions about each of the jobs presented to you. Once again, remember there are no "correct" or "incorrect" decisions in this exercise, so express your true feelings and intentions. You should work briskly without hurrying. Please complete the exercise in a single setting.

NOTICE: The information you provide will be held in strict confidence. Your privacy will be protected.

Job #1

In this job, the likelihood that you will.....

...live in a desirable geographic location is..............VERY HIGH (90%)

...be promoted within two years is..........................MEDIUM (50%)

...receive a salary at an above average level is...........VERY HIGH (90%)

<u>DECISION A</u>. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #2

In this job, the likelihood that you will.....

...live in a desirable geographic location is...............VERY LOW (10%)

...be promoted within two years is..........................MEDIUM (50%)

...receive a salary at an above average level is...........VERY HIGH (90%)

<u>Decision A.</u> With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #3

In this job, the likelihood that you will.....

...live in a desirable geographic location is...............VERY LOW (10%)

...be promoted within two years is.......................VERY HIGH (90%)

...receive a salary at an above average level is..............MEDIUM (50%)

<u>Decision A</u>. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #4

In this job, the likelihood that you will.....

...live in a desirable geographic location is...............VERY LOW (10%)

...be promoted within two years is.........................VERY LOW (10%)

...receive a salary at an above average level is..............MEDIUM (50%)

DECISION A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #5

In this job, the likelihood that you will.....

...live in a desirable geographic location is..............VERY HIGH (90%)

...be promoted within two years is...........................MEDIUM (50%)

...receive a salary at an above average level is............VERY LOW (10%)

Decision A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #6

In this job, the likelihood that you will.....

...live in a desirable geographic location is...............VERY LOW (10%)

...be promoted within two years is.........................VERY LOW (10%)

...receive a salary at an above average level is...........VERY HIGH (90%)

Decision A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #7

In this job, the likelihood that you will.....

...live in a desirable geographic location is...............VERY HIGH (90%)

...be promoted within two years is..........................VERY LOW (10%)

...receive a salary at an above average level is............VERY HIGH (90%)

DECISION A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5
Very Unattractive — Very Attractive

Job #8

In this job, the likelihood that you will.....

...live in a desirable geographic location is..................MEDIUM (50%)

...be promoted within two years is..........................VERY HIGH (90%)

...receive a salary at an above average level is...............MEDIUM (50%)

Decision A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5
Very Unattractive — Very Attractive

Job #9

In this job, the likelihood that you will.....

...live in a desirable geographic location is...............VERY HIGH (90%)

...be promoted within two years is..........................VERY HIGH (90%)

...receive a salary at an above average level is...............MEDIUM (50%)

Decision A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5
Very Unattractive — Very Attractive

Job #10

In this job, the likelihood that you will.....

...live in a desirable geographic location is..............VERY HIGH (90%)

...be promoted within two years is...........................MEDIUM (50%)

...receive a salary at an above average level is..............MEDIUM (50%)

DECISION A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #11

In this job, the likelihood that you will.....

...live in a desirable geographic location is...............VERY LOW (10%)

...be promoted within two years is........................VERY HIGH (90%)

...receive a salary at an above average level is............VERY LOW (10%)

Decision A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #12

In this job, the likelihood that you will.....

...live in a desirable geographic location is..............VERY HIGH (90%)

...be promoted within two years is.........................VERY LOW (10%)

...receive a salary at an above average level is............VERY LOW (10%)

Decision A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #13

In this job, the likelihood that you will.....

...live in a desirable geographic location is..................MEDIUM (50%)

...be promoted within two years is.............................MEDIUM (50%)

...receive a salary at an above average level is...............MEDIUM (50%)

DECISION A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #14

In this job, the likelihood that you will.....

...live in a desirable geographic location is..................MEDIUM (50%)

...be promoted within two years is...........................VERY LOW (10%)

...receive a salary at an above average level is.............VERY LOW (10%)

Decision A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #15

In this job, the likelihood that you will.....

...live in a desirable geographic location is................VERY LOW (10%)

...be promoted within two years is.........................VERY HIGH (90%)

...receive a salary at an above average level is...........VERY HIGH (90%)

Decision A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #16

In this job, the likelihood that you will.....

...live in a desirable geographic location is................VERY LOW (10%)

...be promoted within two years is...........................MEDIUM (50%)

...receive a salary at an above average level is...............MEDIUM (50%)

DECISION A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #17

In this job, the likelihood that you will.....

...live in a desirable geographic location is................VERY LOW (10%)

...be promoted within two years is...........................VERY LOW (10%)

...receive a salary at an above average level is.............VERY LOW (10%)

Decision A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #18

In this job, the likelihood that you will.....

...live in a desirable geographic location is..................MEDIUM (50%)

...be promoted within two years is.........................VERY HIGH (90%)

...receive a salary at an above average level is...........VERY HIGH (90%)

Decision A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #19

In this job, the likelihood that you will.....

...live in a desirable geographic location is...............VERY HIGH (90%)

...be promoted within two years is..........................VERY LOW (10%)

...receive a salary at an above average level is...............MEDIUM (50%)

DECISION A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #20

In this job, the likelihood that you will.....

...live in a desirable geographic location is..................MEDIUM (50%)

...be promoted within two years is..........................VERY LOW (10%)

...receive a salary at an above average level is............VERY HIGH (90%)

Decision A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #21

In this job, the likelihood that you will.....

...live in a desirable geographic location is................VERY LOW (10%)

...be promoted within two years is............................MEDIUM (50%)

...receive a salary at an above average level is............VERY LOW (10%)

Decision A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #22

In this job, the likelihood that you will.....

...live in a desirable geographic location is..................MEDIUM (50%)

...be promoted within two years is...........................MEDIUM (50%)

...receive a salary at an above average level is.............VERY LOW (10%)

<u>DECISION A.</u> With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #23

In this job, the likelihood that you will.....

...live in a desirable geographic location is..................MEDIUM (50%)

...be promoted within two years is..........................VERY LOW (10%)

...receive a salary at an above average level is...............MEDIUM (50%)

<u>Decision A.</u> With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #24

In this job, the likelihood that you will.....

...live in a desirable geographic location is..................MEDIUM (50%)

...be promoted within two years is........................VERY HIGH (90%)

...receive a salary at an above average level is.............VERY LOW (10%)

<u>Decision A.</u> With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
Very Unattractive										Very Attractive

Job #25

In this job, the likelihood that you will.....

...live in a desirable geographic location is...............VERY HIGH (90%)

...be promoted within two years is.........................VERY HIGH (90%)

...receive a salary at an above average level is.............VERY LOW (10%)

DECISION A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5
Very Unattractive ... Very Attractive

Job #26

In this job, the likelihood that you will.....

...live in a desirable geographic location is...............VERY HIGH (90%)

...be promoted within two years is.........................VERY HIGH (90%)

...receive a salary at an above average level is............VERY HIGH (90%)

Decision A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5

Very Unattractive ... Very Attractive

Job #27

In this job, the likelihood that you will.....

...live in a desirable geographic location is..................MEDIUM (50%)

...be promoted within two years is............................MEDIUM (50%)

...receive a salary at an above average level is............VERY HIGH (90%)

Decision A. With the relationships shown above in mind, indicate the attractiveness of this particular job to you.

-5 -4 -3 -2 -1 0 +1 +2 +3 +4 +5
Very Unattractive ... Very Attractive

Appendix C

Derivation of the Sequential Judgment Mathematical Model

The basic mathematical model developed in Chapter III was given in equation 10 as:

$$R_j^* = \frac{\sum_{i=1}^{N}(R_{i-1} - W_i\ (\mathrm{Max}(S_i) - S_i)) - \sum_{i=1}^{N}(R'_{i-1} - W_i\ \mathrm{Max}(S_i)}{N\ \mathrm{Max}(S_i) - \sum_{i=1}^{N} R'_{i-1} - W_i\ \mathrm{Max}(S_i)} \quad . \qquad (C1)$$

Let $M = \mathrm{Max}(S_i)$ represent the maximum score that a decision cue can receive. Note that R_i and R'_i were used to distinguish the decayed rating from the worst case rating. The numerator and denominator can be expressed in terms of the actual decayed rating value Y_i as:

$$R_j^* = \frac{\sum_{i=1}^{N}(Y_{i-1} - W_i\ (M-S_i)) - \sum_{i=1}^{N}(Y_{i-1} - W_iM)}{NM - \sum_{i=1}^{N}(Y_{i-1} - W_iM)} \quad . \qquad (C2)$$

where

R_j^* = the rating given alternative j,

Y_i = the progression of ratings as each cue and weight is brought into the model,

Y_0 = the initial, perfect score,

S_i = the score given each cue i,

M = the maximum score possible across all i cues,

N = the number of decision cues,

W_i = the weight for each cue i.

The numerator of equation C2 can be expanded and terms collected to yield a simplified form:

$$R_j^* = \sum_{i=1}^{N} (N+1-i)\ W_iS_i \quad . \qquad (C3)$$

The denominator can be reduced to

$$R_j^* \text{ Denominator} = M \sum_{i=1}^{N} (N+1-i)W_i \quad . \tag{C4}$$

Combining equations C3 and C4 yields a reduced mathematical formula for the sequential judgment model. This reduced form is given as:

$$R_j^* = \frac{\sum_{i=1}^{N}(N+1-i)\ W_i\ S_i}{M\sum_{i=1}^{N}(N+1-i)\ W_i}\text{, for all j.} \tag{C5}$$

Derivatives can be formulated using equation C5 and applying standard methods of calculus. The derivatives for each decision cue weight, W_i, are equivalent and described by:

$$\frac{dR_j^*}{dW_i} = \frac{[(N+1-i)S_i]\sum_{i=1}^{N}(N+1-i)W_i - (N+1-i)\sum_{i=1}^{N}(N+1-i)W_iS_i}{M\ [\sum_{i=1}^{N}(N+1-i)W_i]^2} \tag{C6}$$

Although equation C6 appears complex, it is in reality a relative measure of a cue's contribution to a rating, R_j^*, at any given value of W_i (the current cue weight). Appendix D presents an implementation of these equations in a SAS model suitable for direct estimation of W_i given a set of S_i for j alternatives. The objective is to minimize the overall error $R_j - R_j^*$ over all j experimental units.

Appendix D

SAS Program Used for Estimating Nonlinear Weights for the Sequential Judgment Model

```
DATA SOYBEANS;
INPUT N RT C1 C2 C3 C4 C5 C6     /* ENTER RATINGS & CRITERIA */;
Y = (RT+5)/10                    /* SCALE RATINGS 0 TO 10 */;
RESV   = (C1+1)/2                /* SCALE RESOURCE CUE */;
GOVV   = (C2+1)/2                /* SCALE GOV SUPPORT CUE */;
PRICEV = (C3+1)/2                /* SCALE PRICE CUE */;
MRKTV  = (C4+1)/2                /* SCALE MARKET CUE */;
YIELDV = (C5+1)/2                /* SCALE YIELD CUE */;
MONEYV = (C6+1)/2                /* SCALE MONEY CUE */;
CARDS                            /* READ DATA FILE */;
PROC SORT                        /* SORT DATA INTO         */;
     BY ID                       /* RESPONDENT ID ORDER    */;
*                                                             ;
* PROC NLIN EXECUTES THE NONLINEAR ESTIMATION PROCEDURE       ;
* INITIALLY, VARIALES ARE SET AT SOME VALUE TO START THE      ;
* PROCEDURE.  DERIVATIVES MUST BE SUPPLIED.                   ;
PROC NLIN METHOD = MARQUARDT     /* EXECUTE NONLINEAR ESTIMATION */;
     PARMS RES=1 GOV=1 PRICE=1 MRKT=1 YIELD=1 MONEY=1;
     MAX=1.0;
     F1=RESV;
     F2=GOVV;
     F3=PRICEV;
     F4=MRKTV;
     F5=YIELDV;
     F6=MONEYV;
     W1=RES;
     W2=GOV;
     W3=PRICE;
     W4=MRKT;
     W5=YIELD;
     W6=MONEY;
     Z1=6*F1*W1;
     Z2=5*F2*W2;
     Z3=4*F3*W3;
     Z4=3*F4*W4;
     Z5=2*F5*W5;
     Z6=F6*W6;
     ZT=Z1+Z2+Z3+Z4+Z5+Z6;
     WC1=6*W1;
     WC2=5*W2;
     WC3=4*W3;
     WC4=3*W4;
     WC5=2*W5;
     WC6=W6;
     WCT=WC1+WC2+WC3+WC4+WC5+WC6;
     WCT2=MAX*WCT;
     MODEL Y = ZT/WCT2;
     DER.RES     =  (6*(WCT*F1 - ZT))/(MAX*WCT**2);
     DER.GOV     =  (5*(WCT*F2 - ZT))/(MAX*WCT**2);
     DER.PRICE   =  (4*(WCT*F3 - ZT))/(MAX*WCT**2);
     DER.MRKT    =  (3*(WCT*F4 - ZT))/(MAX*WCT**2);
     DER.YIELD   =  (2*(WCT*F5 - ZT))/(MAX*WCT**2);
     DER.MONEY   =  (1*(WCT*F6 - ZT))/(MAX*WCT**2);
     OUTPUT OUT=TEMP P=YNLN      /* BUILD DATASET OF PREDICTIONS */;
     BY ID                       /* DO ANALYSIS BY ID NO.        */;
```

Appendix E

An Application of the Sequential Judgment Model to Computer Performance Evaluation

This appendix demonstrates the effectiveness of the sequential judgment model. The decision model is used to judge the relative performance of competing computer architectures based on cues and weights established by the Department of Defense (DoD) during a 1976 study. The objective of the study was to recommend computer systems for detailed testing in order to recommend an architecture for the next decade of defense use.

Computer performance evaluation is an inherently complex and ill defined subject area. The exorbitant cost of extensive testing precludes analysis of each potential candidate machine. Rather, it was desired to determine which of many machines were best qualified for DoD use and then to extensively test those most highly rated machines. This example is taken from the Army-Navy Computer Family Architecture Study (CFA) Project described in detail by Fuller, Stone, and Burr (1977). Siewiorek, Bell, and Newell (1982) summarize the analysis procedure.

Nine computer architectures were considered prime DOD candidates for selection. Each of the nine computer systems was evaluated on both absolute criteria and on quantitative criteria. This example presents the quantitative analysis. Seventeen criteria were determined to be important in ranking the nine computers. These criteria are summarized as:

V1 - the size of the virtual address space in bits,

V2 - the number of addressable units in virtual space,

P1 - the size of the physical address space,

P2 - the number of addressable units in physical space,

U - the fraction of instruction space unassigned, CS1 - the number of bits in the processor state,

CS2 - the number of bits in the minimal architecture,

CM1 - the number of bits transferred between the processor and primary memory on an interrupt,

CM2 - the CM1 for the minimal architecture.

B1 - the number of computers delivered as of June 1976,

B2 - the total dollar value of installed systems,

I - the minimum number of bits transferred per I/O request,

K - is the architecture virtualizable? (0 or 1),

D - the maximum number of bits accessible given one base register,

J1 - the number of bits required to store the status, execute a subroutine and return to the user state,

J2 - the J1 measure for the minimal architecture.

The performance measures combine technical characteristics of computer systems with measures of company performance and stability. The relative weights for the 17 criteria were obtained by requesting each member of the CFA study group to distribute 100 points across the decision cues. Clearly these weights are highly subjective. The individual weights were averaged to yield composite weights shown in Table E1.

Since high values of some criteria are not desirable, a standardization scheme was used to normalize the measures. Since it was desired to minimize CS1, CS2, CM1, CM2, I, L, J1, and J2; these measures are transformed by taking their inverse. The original study group normalized the individual computer ratings by insuring that the mean rating for each cue equaled one. For this example the technique widely applied and discussed by Hwang and Yoon (1981) is employed. The smallest rating for a given cue is subtracted from the computer's rating and then

Table E-1. Quantitative Criteria Weights

Criteria	Average Weight
V1	0.0433
V2	0.0529
P1	0.0612
P2	0.0554
U	0.0600
CS1	0.0466
CS2	0.0371
CM1	0.0596
CM2	0.0450
K	0.0558
B1	0.0313
B2	0.0254
I	0.1238
D	0.1025
L	0.0917
J1	0.0629
J2	0.0475

divided by the range of cue ratings over all computers. This yields a rating for each cue on each computer that falls between 0 and 1. This transformation removes the bias generated by scale differences of the cues.

Table E2 contains the raw data obtained for each computer system. Each alternative computer was rated using the linear and sequential decision models presented in this paper. The weights in Table E1 were used as well as equal weights with the cues included in the order specified by the subjective weights. Based on the findings of this research, the linear model should best use the subjective weights and the sequential model do as well with the equally weighted cues. Table E3 presents the rank order for the decision models as well as the rank order determined by the CFA committee.

It is found that the CFA committee's rank order differs significantly from all of the calculations completed in this research. This is explained by noting that the committee further normalized some cues by fixing the standard deviations and by forcing the average cue rating to unity. These steps result in differences with the simple transformations used here.

The important comparison is between the linear compensatory model and the sequential model given the weights and scores used in this research. Note that subjective weights in the linear model and equal weights in the sequential model produced almost identical results! The implication is that substantial effort could have been saved had equally weighted cues been employed in the sequential decision model.

Table E-2. Candidate Computer System Performance Attributes

Quantitaive Criteria	IBM S/370	Inter-Data 8/32	Rolm AN/UY K-28	DEC PDP-11	Univac AN/UY K-7	SEL 32	Burroughs B6700	Univac AN/UY K-20	Litton AN/GY K-12
V_1	27	20	20	20	24	22	24	20	20
V_2	27	27	20	19	24	22	20	17	20
P_1	27	27	22	25	23	26	24	20	29
P_2	27	27	22	24	23	26	20	17	29
U	.371	.355	.039	.043	.15	.450	.019	.125	.219
C_{s1}	1344	1632	1008	1168	992	304	306	1328	1008
C_{s2}	576	576	112	144	448	288	204	336	752
C_{m1}	3168	1120	1882	736	1472	768	408	2256	1344
C_{m2}	1312	32	544	430	1472	704	408	720	1088
K	1	0	0	1	0	0	0	0	0
B_1	17,300	185	13,800	14,700	346	75	90	400	30
B_2	16,000	14	169	311	147	23	207	8	6
I	64	16	48	16	128	64	169	80	32
D	15	27	20	19	18	22	18	20	20
L	6192	560	114	112	2112	288	255	--	1376
J_1	1904	2368	1360	1040	1280	960	459	1408	1344
J_2	1136	1280	320	400	1280	960	459	640	1088

Table E-3. Rank Order of the Candidate Computer Architectures

Architecture	CFA Analysis	Linear Model	Sequential Model (Equal Weights)
Interdata 8/32	1	1	1
PDP - 11	2	2	2
IBM S/370	3	4	5
Litton AN/GYK-12	4	7	7
Rolm AN/UY K-28	5	6	6
Burroughs B6700	6	4	5
SEL 32	7	3	3
Univac AN/UYK-7	8	8	8
Univac AN/UYK-20	9	9	9

It is concluded that complex decision problems can be formulated as sequential combinations of cues and weights and that equally weighted cues perform quite well.

Appendix F

An Application of the Sequential Judgment Model to Strategic Planning

This appendix contains an application of the sequential judgment model in the general area of strategic planning. Specifically, a model which assesses the industry attractiveness of a potential strategic business unit (SBU) is developed and compared with the linear compensatory model.

Numerous techniques have been developed which are recommended when attempting to access the desirability of a SBU as an acquisition candidate. Usually it is recommended that an extensive analysis of the SBU's strengths and weaknesses be evaluated in light of the acquiring firm's competitive strategy. One popular method developed by General Electric is the GE Business Screen. The screen consists of measuring the SBU characteristics in terms of industry attractiveness and competitive position. Each of these measures consists of many attributes which are evaluated to form a single metric and plotted on the business screen.

Hofer and Schendel (1978) discuss this technique and present suggested attributes for both industry attractiveness and competitive position. They suggest the use of linear compensatory models for combining the attributes and their weights into single performance measures. Several problems are discussed by the authors.

First, the choice of attributes or decision cues is difficult due to the complex and uncertain nature of corporate strategy. The decision model is dependent on purely subjective insight of individuals involved in the acquisition project.

Second, the choice of weights for the decision cues is entirely subjective. Furthermore, the weights should change as alternate SBU's in different industries are considered. For example, the weight for R & D should be quite different for an electronics firm versus a textile plant because of the inherent differences in the industry's dependence on research.

Finally, the attributes are often measured in both relative and absolute terms. That is, objective data such as industry profitability is measurable while energy impact is a subjective rating. How are these measurements to be combined in a decision model? Hofer and Schendel recommend using objective data when possible with explicit rating schemes and requiring collective judgments of experienced decision makers.

Table F1 presents the set of industry attractiveness criteria suggested by Hofer and Schendel. The weight attached with each attribute is shown. Note that some attributes are binary cues. That is, the SBU must be judged acceptable on those cues before continuing additional analysis.

Consider the comparison of two SBU's which are in industries A and B respectively. It is desired to evaluate the industry attractiveness of each SBU. Following this analysis a similar decision model would be completed for each SBU's competitive position and the SBU measures plotted on the GE Business Screen. This example will demonstrate only the industry attractiveness model to present the application of the sequential judgment model.

Table F2 presents the weighted scores of SBU A and B for the industry attractiveness measure. Note that while the industries are quite different the overall ratings are the same. The critical question is whether or not the linear model made the test use of the specified criteria weights.

Table F-1. Industry Attractiveness Criteria (Hofer and Schendel, 1982)

Criteria	Weight
Size	0.15
Growth	0.12
Pricing	0.05
Market Diversity	0.05
Competitive Structure	0.05
Industry Profitability	0.20
Technical Role	0.05
Inflation Vulnerability	0.05
Cyclicality	0.05
Customer Financials	0.10
Energy Impact	0.08
Human	0.05
Social	GO/NoGo
Environmental	Go/NoGo
Legal	Go/NoGo
TOTAL	1.00

Table F-2. Industry Attractiveness Measured by the Linear Model

Criteria	Weight	SBU A Score*	SBU B Rating	SBU B Score*	SBU B Rating
Size	0.15	4	0.60	3	0.45
Growth	0.12	3	0.36	2	0.24
Pricing	0.05	3	0.15	4	0.20
Market Diversity	0.05	2	0.10	4	0.20
Competitive Structure	0.05	3	0.15	4	0.20
Industry Profitability	0.20	3	0.60	2	0.40
Technical Role	0.05	4	0.20	5	0.25
Inflation Vulnerability	0.05	2	0.10	5	0.25
Cyclicality	0.05	4	0.20	5	0.25
Customer Financials	0.10	4	0.40	4	0.40
Energy Impact	0.08	4	0.32	3	0.24
Human	0.05	3	0.15	5	0.25
TOTALS	1.00		3.33		3.33
RELATIVE RATING			0.67		0.67

*The score is 1 = very unattractive and 5 = very attractive.

Two possibilities exist when using the sequential model. First, it could be assumed that the weights specified by Hofer and Schendel are correct and specify the importance of the decision cues. If so, then the weights should be used to rank order the criteria and applied in the sequential model. Table F3 presents the results of this approach.

The other possibility is that the decision cues are correct but that the weights are highly subjective. At best the weights reflect the rank order of the decision cues. Given the demonstrated performance of the sequential judgment model, the cues should be rank ordered by the subjective weights and then equally weighted. Table F4 presents the results of this possibility.

Several observations are evident. The linear compensatory decision model yielded ratings that were equivalent in terms of industry attractiveness. Both SBU's scored an overall 67% of a possible perfect industry. If it is assumed that the weights are correct and not subject to estimation or specification error the sequential model reached very different ratings. Table F3 indicates that the rating for SBU A is 68% versus 59% for SBU B.

The disparity is explained by noting that SBU A consistently performed better in every highly weighted attribute of industry attractiveness. Clearly, the sequential model processed knowledge of the importance of a cue differently than a linear compensatory model. It is argued that the specification of weights a priori is a reflection of an underlying decision making strategy. When weights are known or specified the sequential judgment model insures that the effects of highly weighted cues are considered first. This process results in

Table F-3. Industry Attractiveness Measured by the Sequential Judgment Model with Specified Weights

Criteria	Weight	SBU A Score*	SBU B Rating	SBU B Score*	SBU B Rating
Industry Profitability	0.20	3	4.60	2	4.40
Size	0.15	4	4.45	3	4.10
Growth	0.12	3	4.21	2	3.74
Customer Financials	0.10	4	4.11	4	3.64
Energy Impact	0.08	4	4.03	3	3.48
Technical Role	0.05	4	3.98	5	3.48
Market Diversity	0.05	2	3.83	4	3.43
Competitive Structure	0.05	3	3.73	4	3.38
Cyclicality	0.05	4	3.68	5	3.38
Inflation Vulnerability	0.05	2	3.53	5	3.38
Pricing	0.05	3	3.43	4	3.33
Human	0.05	3	3.33	5	3.33
TOTALS	1.00		46.91		43.07
RATING ADJUSTED FOR WORST CASE			0.68		0.59

*The score is 1 = very unattractive and 5 = very attractive.

Table F-4. Industry Attractiveness Measured by the Sequential Judgment Model with Equal Weights

Criteria	Weight	SBU A Score*	SBU B Rating	SBU B Score*	SBU B Rating
Industry Profitability	0.08	3	4.83	2	4.75
Size	0.08	4	4.75	3	4.58
Growth	0.08	3	4.58	2	4.33
Customer Financials	0.08	4	4.50	4	4.25
Energy Impact	0.08	4	4.42	3	4.08
Technical Role	0.08	4	4.33	5	4.08
Market Diversity	0.08	2	4.08	4	4.00
Competitive Structure	0.08	3	3.92	4	3.92
Cyclicality	0.08	4	3.83	5	3.92
Inflation Vulnerability	0.08	2	3.58	5	3.92
Pricing	0.08	3	3.42	4	3.83
Human	0.08	3	3.25	5	3.83
TOTALS	1.00		49.50		49.50
RATING ADJUSTED FOR WORST CASE			0.68		0.68

*The score is 1 = very unattractive and 5 = very attractive.

ratings of competing alternatives which more closely resemble the actual decision making behavior of human judges.

If the weights are assumed to be subjective weights subject to error, then use of equal weighted cues in the sequential model is advised. The concern is that asking decision makers their relative weights is highly error prone. A better technique would be to ask for rank ordering of the cues or pairwise comparisons via the theory developed by Saaty (1982). If the subjective weights are used to rank order the cues and then equal weights applied, the results shown in Table F4 indicate equivalent ratings for SBU A and SBU B. This conclusion is the same as the linear decision model but based on the most efficient estimation of cue weights known; set them equal!

In summary it is recommended that in the absence of specified weights, asking decision makers to rank order decision cues and use of the sequential model yields effective results. When weights are known the sequential model makes better use of the weights to mirror more closely the behavior of decision makers. Certainly the choice of a decision model is a prime consideration since ratings differ between alternative models and result in significantly different positions for each SBU on the GE Business Screen.

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